INFRASTRUCTURE MEDIATED SENSING

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INFRASTRUCTURE MEDIATED SENSING

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To my family, now and to come, for their love and support

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LIST OF SYMBOLS AND ABBREVIATIONS

ADA	Americans with Disabilities Act
ADL	Activities of Daily Living
BPL	Broadband over Powerline
BT	Bluetooth
CATEA	Center for Assistive Technology and Environmental Access
CHIEF	Craig Hospital Inventory of Environmental Factors
DDS	Distributed Direct Sensing
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HAS	Home Accessibility Survey
HVAC	Heating, Ventilation, and Air Conditioning
ICF	International Classification of Functioning, Disability and Health
IMS	Infrastructure Mediated Sensing
J2ME	Java 2, Micro Edition
KNN	K-Nearest Neighbors
NEC	National Electric Code
PLP	PowerLine Positioning
RSSI	Received Signal Strength Indicator

SUMMARY

Ubiquitous computing application developers have limited options for a practical activity and location sensing technology that is easy-to-deploy and cost-effective. In this dissertation, I have developed a class of activity monitoring systems called infrastructure mediated sensing (IMS), which provides a whole-house solution for sensing activity and the location of people and objects. Infrastructure mediated sensing leverages existing home infrastructure (*e.g*, electrical systems, air conditioning systems, *etc.*) to mediate the transduction of events. In these systems, infrastructure activity is used as a proxy for a human activity involving the infrastructure. A primary goal of this type of system is to reduce economic, aesthetic, installation, and maintenance barriers to adoption by reducing the cost and complexity of deploying and maintaining the activity sensing hardware. I discuss the design, development, and applications of various IMS-based activity and location sensing technologies that leverage the following existing infrastructures: wireless Bluetooth signals, power lines, and central heating, ventilation, and air conditioning (HVAC) systems. In addition, I show how these technologies facilitate automatic and unobtrusive sensing and data collection for researchers or application developers interested in conducting large-scale *in-situ* location-based studies in the home.

CHAPTER 1

INTRODUCTION AND MOTIVATION

The development of low-cost and easy-to-deploy sensing systems to support activity detection in the home has been an important trend in the ubiquitous computing community. Much of this research has centered on the deployment of a network of inexpensive sensors throughout the home, such as motion detectors or simple contact switches. Although these solutions are cost-effective on an individual sensor basis, they are not without some important drawbacks that limit their desirability as research tools as well as their likelihood of eventual commercial success through broad consumer acceptance.

I have developed an important new class of activity monitoring systems that I call ***infrastructure mediated sensing (IMS),*** which provides a whole-house solution for sensing the activity and location of people and objects. Infrastructure mediated sensing leverages existing home infrastructure, such as the plumbing or electrical systems, to mediate the transduction of events. In these systems, infrastructure activity is used as a proxy for a human activity involving the infrastructure. A primary goal of this type of system is to reduce economic, aesthetic, installation, and maintenance barriers to adoption by reducing the cost and complexity of deploying and maintaining the activity sensing infrastructure.

In this dissertation, I present the design, development, and applications of IMS-based activity and location sensing technologies that leverage existing infrastructure, such as wireless Bluetooth signals, power lines, and central heating, ventilation, and air conditioning (HVAC) systems.

1.1 Sensing Approaches

Two approaches have recently emerged in the research community for studying human activity in the home setting. The first approach involves approximating the actual home environment with a “living laboratory," which is equipped with a rich set of sensors, network infrastructure, and computing resources. Because of their purpose-built nature, living laboratories, such as the Aware Home [61] at Georgia Tech and the PlaceLab [57] at MIT, allow the deployment of a virtually unlimited variety of sensors to capture human activity inside the home. Sensor infrastructure deployed in a living laboratory can be experimental in nature and does not need to meet the cost, stability, robustness, scalability, aesthetics, or maintenance constraints that would confront a sensor system suitable for deployment by an ordinary consumer in his or her own home.

Using the living laboratory approach, researchers have begun to identify a wide range of human-centered computing applications that interact with people by detecting and classifying human activity in the home and reacting to that activity in a way that provides important benefits to the human. For example, researchers have demonstrated systems for providing peace of mind to caregivers of elderly people living alone [23, 83], assisting caregivers of children with developmental disorders [62], as well as systems for chronic disease management [73] and exercise monitoring [21]. To enable these systems, a wide variety of sensors have been deployed in the living laboratory environment to observe a wide variety of variables that are then classified and used as proxies for ordinary human activities. I call this sensing approach "distributed direct sensing," or

DDS. Commonly used DDS devices include high fidelity sensors, such as cameras and microphones, as well as low fidelity sensors such as pressure sensitive floor tiles, passive infrared (PIR) motion detectors, RFID readers, *etc.* distributed throughout the living laboratory. In general, because large numbers of sensors are distributed throughout the environment, special networking infrastructure (either wired or wireless) is installed in the living laboratory to collect sensor data and transport it from the sensor location to special computation and data storage resources that are part of the research infrastructure.

During an experiment in a living laboratory, researchers can constantly monitor the sensing, processing, and storage infrastructure to ensure that it is working properly and that the desired data is being obtained. If a sensor malfunctions, the researcher can repair it and adjust the study parameters to compensate for the temporary loss of data. This approach, while extremely valuable for developing applications in a controlled setting, does not provide high quality data about the real-world utility of the applications that are developed, because the DDS approach is generally too costly and/or too complex to permit widespread deployment.

In recognition of the limitations of the living laboratory approach, some researchers have recently turned their attention to a second approach, involving the creation of deployable versions of sensing technology so that human activity can be studied in more natural and authentic settings, including real homes. There is a strong desire in the research community to demonstrate the value of applications in real-world settings so that research applications can take the leap from the lab to mass deployment. Consequently, identifying a widely accepted, cost-effective, and deployable sensing infrastructure that can easily be added to an ordinary home has become of paramount importance. Some researchers have experimented with sensors that are built into (or built from) widely used digital devices, such as cameras or Bluetooth radios in cellphones [30], or the accelerometers that are built into popular game consoles.

The attractiveness of this approach is that millions of these consumer devices have been sold worldwide, and they are highly refined and well understood technologies that are accessible to people across a wide variety of demographics. These devices are not always carried around the home, however, and they are particularly poorly adopted by the elderly and by disabled people, so they are not a viable source of sensor data for human activity monitoring among these groups of people who stand to benefit most from activity aware applications.

To overcome the challenge of obtaining human activity data in a widely deployable fashion, several researchers have recently begun working on a technique that I call Infrastructure Mediated Sensing, or IMS. Infrastructure mediation refers to the use of existing home infrastructure to sense human activity through the detection and classification of human interaction with that infrastructure. I have identified the home electrical system, plumbing system, heating, ventilation, and air conditioning (HVAC) system, natural gas piping, and computer network (whether wired or WiFi) as widely deployed, existing infrastructure buses where initial experiments have shown that we can sense human generated events caused by interaction with those buses. I informally refer to IMS as "home bus snooping" by analogy to computer network snooping.

There are several important distinguishing features between DDS and IMS, as shown in Figure 1. Distributed direct sensing involves the installation of a new sensing infrastructure into the home. This sensing infrastructure directly senses the presence, motion, or activities of its residents through sensors that are physically located in each space where activity is occurring. Example systems include a new set of sensors and an associated sensor network to transfer the sensor data to a centralized monitoring system where sensor fusion and activity inference take place. In contrast, infrastructure mediated sensing leverages existing home infrastructure, such as the plumbing or electrical systems, to mediate the transduction of events. In IMS systems, infrastructure activity is used as a proxy for a human activity involving the infrastructure. Thus, one of the aims of IMS is to reduce the installation and maintenance barriers to adoption by reducing the cost and complexity of deploying and maintaining the activity sensing infrastructure.

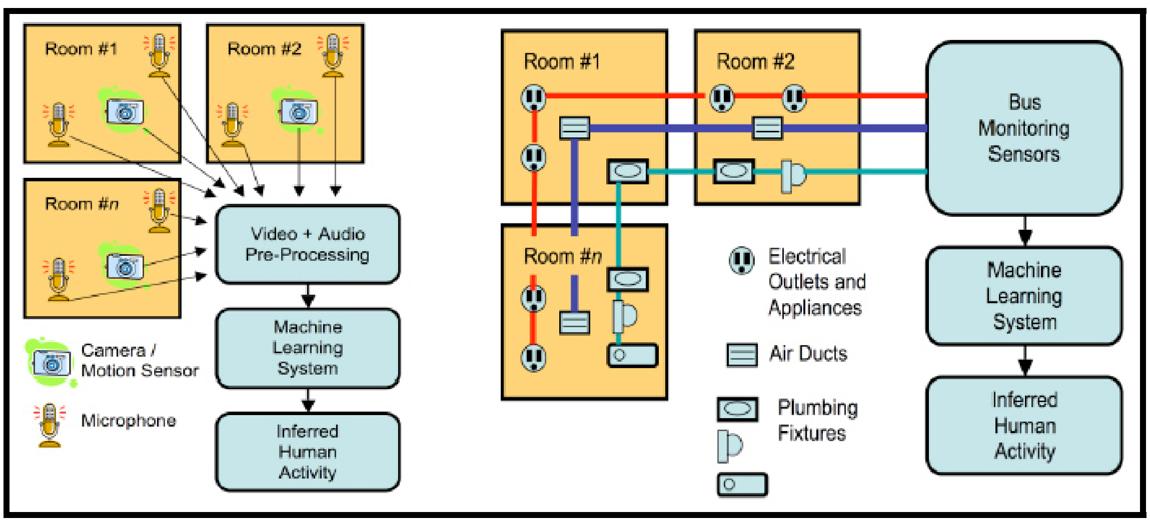


Figure 1: The distributed direct sensing (DDS) approach for activity detection and classification (left). The infrastructure mediated sensing approach for activity detection and classification (right).

1.2 Sample Application Scenario of Sensing

Understanding the interaction between people and objects in their natural setting has been of great interest to researchers for many years. This desire has lead to the use of a variety of investigational techniques such as self-report, experience sampling, and qualitative methods. However, these techniques have limitations when used alone. Self-report is limited to how much information a person can recall in detail. Experience sampling mitigates this problem by probing at the time of the phenomenon, but user burden limits the number of samples researchers can obtain [22]. In addition, individuals with physical or motor impairments have a harder time responding to these kinds of requests. Although human observation provides rich data, it is often time-consuming and not practical for certain environments, such as in the home. Experience sampling and qualitative methods in certain situations are also prone to cause changes in the behavior being investigated.

To address these challenges, technological solutions that employ automatic and unobtrusive sensing and data collection are appealing for a variety of reasons. First, they enable passive data gathering throughout an entire day for an extended period of time. Second, its ability to scale provides a means to generalize results. Finally, sensed data can be coupled with other investigational methods, such as interviews, to obtain more targeted questions.

Despite the appeal of automatic sensing, most researchers *today* who wish to automatically gather sensor information find it to be a difficult and costly endeavor. Often, investigators spend more time struggling with finding the proper technology than with conducting the study itself. As a result, past studies have been limited to laboratory settings, a single laboriously instrumented setting, or a compromise in the use of a lower quality sensing approach.

One important piece of sensed information is the knowledge of the location of people and objects in some setting. This can either be in the form of an absolute position in a space or a relative position between entities of interest. Despite some limitations, Global Positioning System (GPS) is currently the technology of choice for outdoor positioning. However, no single, easy-to-use and cost-effective solution exists for indoor environments, especially for the home. Although sensing platforms are beginning to emerge, they have largely been designed for specific behaviors or require the installation of many sensors to provide simple location information. Thus, investigators who want to conduct long-term, in-home studies or build applications relating to the location of objects and people have limited options for an indoor positioning technology that is easy-to-deploy and cost-effective.

1.3 Purpose of Research and Thesis Statement

I believe there is great value in developing a practical new approach to activity and location sensing systems to support researchers interested in deploying applications in natural settings. They can allow for the automatic collection of objective data to support a variety of applications. Second, it becomes possible to support applications for longer periods of time and to scale to support many simultaneous deployments. Finally, reducing the deployment burden greatly increases the likelihood of a system's ultimate viability and success. Thus, a system must be cost-effective and easy-to-deploy. This is especially important in the case of in-home application.

Having recognized the limitations of current indoor activity and positioning systems, I present the development of a class of a sensing called infrastructure mediated sensing (IMS). I discuss four different IMS systems I have built. The first, called Power Line Positioning (PLP), is an indoor localization system that uses the powerline infrastructure to provide the absolute tracking of people and objects in a home. The second, BlueTrack, leverages existing Bluetooth radio signals for determining relative distances between devices. Next, PowerLine Event Detection, features a single, plug-in sensor capable of detecting and classifying the actuation of specific electrical devices attached to the electrical power lines. The final system is a whole-house solution for detecting gross movement and room transitions by sensing differential air pressure at a single point in the home by leveraging the central heating, ventilation, and air conditioning (HVAC) systems found in many homes.

I present an evaluation that consists of two parts. The first is a technical evaluation of all the technologies to determine the performance and operational parameters. The second involves deployments of this technology. I also present two applications and case studies that use PowerLine Positioning and BlueTrack as a tool for investigators interested in studying people in natural spaces. These case studies are used to evaluate the technology's deployment issues (*e.g.,* time, cost, ease of use, *etc.*), the quality of the resulting data, and the effectiveness in answering the investigator's original questions.

I present the following thesis statement: *(1) Infrastructure Mediated Sensing (IMS) enables practical activity and location sensing by leveraging existing infrastructure in the physical environment. Two particular IMS-based solutions, the PowerLine Positioning and the BlueTrack systems, (2) enable investigators to perform location and proximity-based studies of objects and people in their natural setting and (3) are more cost-effective and are easier to deploy compared to other similar technologies. The systems automatically collect quantitative positioning data of tracked entities which (4) is more accurate than data from self-report methods and allows for a* *prompted mixed-method interview approach that enhances the quality of the gathered data over self-report alone.*

1.4 Research Questions

With this dissertation, I address the following broad questions:

- How do we provide a practical indoor activity and location system that requires minimal infrastructure, is easy-to-deploy, and is cost-effective?
- What are alternative ways to provide location information outside the home in unconstrained environments?
- What is a generalized sensing approach that enables large-scale deployments in the home environment?
- What types of application do these technologies enable and how does the limitation of the technology dictate the type of application that can be designed?
- How can researchers use these sensing technologies as a tool for studying people and objects in a natural setting?
- What value does automatically collected data have, and how can it be coupled with existing investigation methods to produce a mixed-method approach?

1.5 Dissertation Overview

In this dissertation, I present an important new class of activity monitoring systems that I call ***infrastructure mediated sensing (IMS)***, which incorporates minimal monitoring or probing points on an existing home infrastructure (electrical, plumbing, HVAC, *etc.*) or signals from existing systems (WiFi, Bluetooth, *etc.*) to detect human activity throughout the entire space.

I further define this new category of sensing and explain the theory and implementation of four different IMS-based systems. The first is Power Line Positioning (PLP), which is a novel indoor localization system that uses the powerline infrastructure to provide the absolute tracking of people and objects in a home. The second is BlueTrack, which leverages existing Bluetooth radio signal for determining relative distances between devices. Next, PowerLine Event Detection, is a system that features a single plug-in sensor capable of detecting and classifying the actuation of specific electrical devices attached to the electrical power lines. The last system is a whole-house solution for detecting gross movement and room transitions by sensing differential air pressure at a single point in the home by leveraging the central heating, ventilation, and air conditioning (HVAC) systems found in many homes. I also discuss further the application of the PLP and BlueTrack technologies in two case studies, where each technology was used as tool for collecting data and conducting interviews for *in-situ* studies.

PLP is an inexpensive system that uses the powerline infrastructure in a home. It requires only the addition of two plug-in modules to track simple location tags down to one meter. BlueTrack is a Bluetooth-based proximity tracking system that can determine three levels of proximity between custom Bluetooth tags and Bluetooth-enabled devices passively and without the need for active pairing between devices. I conducted technical evaluations of both systems. I gathered various performance measures of PowerLine Positioning from a number of in-home installations to gather its operational parameters. The performance of BlueTrack was evaluated in the laboratory for its proximity prediction accuracy. In addition, two diary studies were used to evaluate the accuracy of BlueTrack in a more natural setting.

I present two of my research studies that use PowerLine Positioning and BlueTrack. With these two deployment studies, I show the type of studies these technologies enable, the deployment issues of the technologies, the quality of the automatically gathered quantitative data compared to traditional self-report methods, and the improvement of the quality of data when applying the mixed-method approach using the tracking data.

The first study is an in-depth, empirical investigation of proximity of the mobile phone to its owner over several weeks of continual observation. The aim of this study was to determine if the mobile phone is a suitable proxy for its owner, understand the reasons behind separation between the user and the mobile phone, and offer guidelines for building mobile phone applications. From this study, I show that BlueTrack offered several key advantages. It allowed the continuous recording of the user's distance to their phone and the gathering of quantitative data not otherwise possible with other investigational means. Additionally, the quantitative data I was able to collect allowed me to explore whether it was possible to apply machine learning techniques to the proximity behavior. Finally, there was little modification to the user's natural behavior during the investigation, and the resulting quantitative proximity traces proved valuable during the mixed-method interview process and the final analysis.

The second study is the deployment of PowerLine Positioning to study the activity of wheelchair users in their homes. In collaboration with researchers at the Center for Assistive Technology and Environmental Access (CATEA) at Georgia Tech, I conducted a study that looks at mobility patterns of wheelchair users in the home. My aims were to determine the in-home environmental factors that promote or hinder mobility, where users spend much of their time in the home, locations where users do not go, and when and where they transition between multiple ambulatory devices. Currently, the practice within the mobility disability research community is to employ self-report. However, self-report often does not give researchers the level of detail necessary for their investigation. In the past, CATEA also struggled to find a practical indoor positioning system capable of meeting their accuracy and ease-of-deployment needs. I used PowerLine Positioning to collect data on the usage of ambulatory and mobility devices in the home. I used this data to obtain a more detailed and objective understanding of mobility patterns over a longer period of time. I also used the gathered location data to conduct more effective interviews with participants. I show that the mixed-method approach results in the identification of more environment barriers and mobility issues in the home when compared to the current best practice of self-report. In addition, I also use this study to evaluate the deployment issues of PowerLine Positioning in terms of installation, removal time, and its ease of use for the researcher.

In Table 1 and Table 2, I show the questions that arise from my thesis claims and how I address those claims with the various deployment studies. The tables merely highlight the key questions and key parts of the studies that I address later in this dissertation.

Table 1: Summary of how the questions relating to the viability of IMS are validated.

	PLP	BlueTrack	PowerLine Event Dection	HVAC-based Tracking
How does one provide a practical indoor activity and location system that requires minimal infrastructure, is easy-to-deploy, and is cost-effective?	- Development and deployment of these technologies - Performance analysis in real-world deployments			

Table 2: Summary of how the questions relating to the application of IMS-based solution are validated

	PowerLine Positioning	BlueTrack
How do these technologies support location or proximity-based studies in a natural setting? What kind of studies do they support?	-CATEA Study: Studying mobility patterns of wheelchair users in their homes -The technical evaluation helps show the types of studies this technology can support and its limitations	-Mobile Phone Proximity Study -The technical evaluation helps show the types of studies this technology can support and its limitations
Are they easier to deploy and less time-consuming to deploy than other similar technologies used for these kind of studies	-I had other individuals conduct the technology installation for the CATEA study to evaluate deployment time and ease of use	-Other researchers and I have deployed this technology and deployment times were noted for each
Can these technologies provide objective measures that can be coupled with the interview process to produce richer and more accurate data than self-report alone?	-CATEA Study: I gathered data using the current practice in the mobility disability community (self-report). I also gathered objective data using the PLP technology and use it during the interviews to evaluate the increase in the richness and quality of the data over self-report.	-Mobile Phone Proximity Study: I gathered data using self-report and then compared it to data I gathered from the BT technology along with interviews -Comparative measures between the quantitative results from the self-report data and the proximity data

CHAPTER 2

BACKGROUND AND RELATED WORK

In this chapter, I first discuss background work related to activity and location sensing technologies. Next, I discuss the applications of current sensing techniques related to conducting studies in the home. I also provide background and related work for the two domains where my technology was applied: studying mobile phone usage and studying the usage of ambulatory devices in the home.

2.1 Indoor Positioning Systems

Indoor positioning has been a very active area of research in ubicomp for the past decade, and many commercial systems are beginning to emerge. Several characteristics distinguish different solutions, such as the underlying signaling technology (*e.g.,* IR, RF, load sensing, computer vision, or audition), line-of-sight requirements, accuracy, and cost of scaling the solution over space and over number of items. Hightower and Borriello provide a thorough overview of indoor positioning systems and techniques [49].

The earliest indoor solutions introduced new infrastructure to support localization [2, 45, 46, 91, 108, 110, 111, 130]. Despite some success, as indicated by commercialized products [32, 54, 126, 128], the cost and effort of installation are a major drawback to wide-scale deployment, particularly in domestic settings. Thus, new projects in location-based systems research reuse existing infrastructure to ease the burden of deployment and lower the cost. The earliest demonstrations leveraged 802.11 access points [8, 67], and more recent examples explore Bluetooth [71] and wireless telephony infrastructure, such as GSM [38, 66, 93] or FM transmission towers [65]. A concern is that individuals may not be able to control the characteristics of this infrastructure and the operational parameters of the infrastructure may change without warning, resulting in the need to recalibrate. The desire to control the infrastructure and to scale inexpensively to track a large number of objects inspired the work on the Powerline Positioning system.

Traditional wireless signal triangulation, such as 802.11 access point triangulation, uses Received Signal Strength Indicator (RSSI) information to estimate distance and determine a location based on its geometric calculations Other techniques include the use of Time of Arrival, as in the case of ultrasound, or Angle of Arrival, such as with Ultra-wideband positioning [126]. Ultrasonic solutions, such as Cricket [108] and Active Bat [2], provide precise centimeter resolution, but require line-of-sight operation indoors. Therefore, they require considerable sensor installations for full coverage. Technologies that avoid issues of occlusion, such as 802.11 triangulation, suffer from multipath problems caused by reflections in the environment.

Fingerprinting of the received signals can help overcome the multipath problem [63]. Fingerprinting improves on other means of estimation by taking into account the effects that buildings, solid objects, or people may have on a wireless or RF signal, such as reflection and attenuation. Fingerprinting works by recording the characteristics of wireless signals at a given position and later inferring that position when the same signature is seen again. A survey of signals over some space allows for the creation of a map that can be used to relate a signal fingerprint to a location.

Many commercial indoor positioning systems have also emerged over the last decade. Ekahau is a WiFi-based positioning system that offers 3-5 meter resolution using six enterprise WiFi access points [32]. Ubisense's ultra-wideband system [126] offers higher precision at about 15 cm; however, it involves a tedious installation process. Indoor GPS [54] and the Crossbow Mica Cricket [27] system offer even better precision, however, they require a line-of-sight view of the transponders installed in the environment.

2.2 Detecting and Studying Proximity

The design of the BlueTrack proximity detection system was partially inspired by the SPECs project at HP Labs [70], which demonstrated how simple peer-to-peer wireless devices can be used to collect proximity information to recognize certain activities. In the case of SPECs, infrared technology was used to build applications that can take advantage of proximity knowledge of a collection of devices. The disadvantage to this approach is the sensors must be exposed and within line-of-sight between devices. In my case, I use RF-based Bluetooth technology and take advantage of the Bluetooth on the phone and other Bluetooth-enabled devices to collect data that describes everyday phenomena, such as which portions of a day individuals are within arm's reach of their mobile phone. In addition, the BlueTrack system can provide information regarding the proximity measure (three levels) between devices.

A recent redesign of the SPECs system, called FireFly [35], replaces the IR sensor with an RF sensor, which mitigates the line-of-sight problem. Similar to my aim with BlueTrack, the sensing platform aims to gather information about the physical context and behavior of people and objects automatically and continually. However, the drawback of the FireFly system is that it currently only supports the detection of the identity of a tagged device in its detectable range and does not provide any ranging measurements. Also, the current FireFly system costs approximately $5,000 USD for 10 sensors. The reason for the high cost is the use of proprietary radio hardware and low production numbers. The BlueTrack system uses a much higher production Bluetooth radio system, thus has a much better advantage in terms of cost and production. In addition, the BlueTrack system interoperates with other Bluetooth-enabled devices without the need for additional instrumentation, whereas the FireFly system would require each device of interest to be tagged.

Hazas *et al.* demonstrate a system capable of fine-grained, relative position information to co-located devices using peer-to-peer sensing, thus overcoming dependence on any external infrastructure [44]. The system uses ultrasound for sensing both distance and orientation to other devices. The limitation of this system is its requirement of line-of-sight between the sensors. However, when line-of-sight is achieved, they claim accuracies of about 10 cm in distance and 33 degrees in orientation.

In the wireless sensor network community, there have been many general purpose, peer-to-peer sensor nodes that support proximity detection between nodes, such as the Berkeley/Mica Motes [80], Smart Dust [121], and SmartIts [12], They often have a received signal strength indicator (RSSI) value to estimate physical distance between nodes. Similarly to the peer-to-peer systems discussed above, they often incorporate proprietary radios. However, Bluetooth enabled sensor nodes are beginning to emerge such as the BTnode from ETH Zurich [13].

There has been extensive research in the area of using Bluetooth-enabled devices, namely mobile phones, to detect the social space of nearby Bluetooth devices and later offer services when that social space is encountered again [30, 31, 87, 97, 106, 113, 125].

One particular application, called BlueAware, senses unique Bluetooth MAC addresses and logs them to a text file [31]. The application queries a server with a discovered address, and the server associates the address with an individual's online profile. A similarity metric is generated between the two people, and, depending on both users' settings, the server alerts them of their proximity and common interests. The Jabberwocky mobile phone application seeks to promote a sense of familiarity in an urban community [97]. The application stores any proximate Bluetooth devices it encounters and provides a visualization to indicate the level of familiarity at a given location. These applications could benefit from using the ranging capabilities of the BlueTrack software to provide a little more detail to the proximity information. The advantage of BlueTrack is that it does not require any pairing between Bluetooth devices, thus it can run passively like the aforementioned applications.

Researchers have developed methods for detecting face-to-face interaction to study human communication dynamics. The Sociometer is a wearable sensor pack that is capable of logging when other people wearing the same sensor are nearby and storing audio information for post processing [17, 18]. This system has been used to model social interaction within a group of individuals. Similar work has also looked at using proximity to learn how social groups form [19].

Researchers have also looked at using the proximity user’s mobile devices to personal computers for authentication [20]. For years, people have envisioned a mobile phone that can sense the availability of its owner and adjust its ring tone to be socially appropriate. Researchers have even speculated about how availability information can be communicated at a distance, so that a potential caller can choose an appropriate time to interrupt someone else [86, 104, 105].

2.3 Powerline Research

Power lines are already in place in most homes, and the power network reaches more homes than either cable systems or telephone lines. Thus, for many years, people have been using power lines in homes to deliver more than just electricity. Several home technologies leverage the power line for communications and control. The most popular example is the X10 control protocol for home automation, a standard that is more than 30 years old and is a very popular, low-cost alternative for homeowners. Over the past decade, there has been a number of efforts to produce powerline communications capabilities, driven by industrial consortia like HomePlug Powerline Alliance [51], and efforts such as Broadband over Powerline (BPL).

2.4 Studying People and Objects in the Home

With the advent of new, affordable technologies, there has been a trend in research to shift from building technology to supporting office life to supporting home life. Abowd and Mynatt describe a need for studying domestic settings to inform the design of new technologies [1]. Edwards and Grinter echo similar sentiments in that people are using technologies in new and interesting ways in the home [34]. Thus, a key research problem for designing for the home is first to study the everyday workings of the home, such as how people live in the home, what they do, and the role that technologies play.

The initial foray in studying the home has been with ethnography. For example, Crabtree and Rodden present a series of ethnographic studies that aimed to uncover communication routines and how people use particular spaces in the home [25, 26]. They provide guidelines for placing technology in appropriate locations in the home. Other work has included deploying cultural probes in order to analyze home life in a creative a way [48].

Intille *et al.* present techniques for acquiring data about people, their behavior, and their use of technology in a natural setting [56]. One is a context-aware experience sampling method, which extends electronic experience sampling to proactively trigger data collection when certain phenomena. They use simple state-change sensors that can be quickly installed throughout nearly any environment to collect information about patterns of activity. They also describe a tool called image-based experience sampling that allows users to annotate particular video segments of a situation shortly after it has happened.

With the proliferation of portable electronic devices in the home, researchers are interested in studying the complex interactions between household residents and their devices. Aipperspach *et al.* looked at using sensor-based visual records of the physical movement of people and devices to facilitate in-depth discussion during interviews [4, 5]. They are interested in the use of portable computing devices in the context of their location in the home and the people around them. They have presented promising initial results in that the location data provided effective prompts during the interview. In their studies, they use the Ubisense ultra-wideband (UWB) tracking system, which has some disadvantages. Because of the broad spectrum range of UWB devices, their use is currently quite limited by government regulatory agencies. Thus, it is required obtain acquire a temporary waiver from the United States Federal Communications Commission

(FCC). Other drawbacks of Ubisense are its time-consuming installation process and its cost, which is about $10,000 USD for a standard house, and it is not guaranteed to cover the entire home. PowerLine Positioning can potentially address this need for an easy-to-deploy and cost-effective location system. The deployment of PowerLine Positioning shows how well it works as tool for investigators, similar in spirit to the work at Intel.

Recent work has also highlighted the need to further explore the role of location in the home and its impact on technology. For example, Elliott *et al.* found that people used location in interesting ways in sharing information within the household, often using many different locations to convey different meanings [33]. O'Brien *et al.* argue at a more general level that an understanding of domestic patterns can be a good motivator for design [90]. Researchers have also shown that people can be inaccurate at reporting their own use of space, thus arguing for more objective measures, such as sensing technology [72]. In addition, many researchers are now exploring the role of location and other sensor measurements in health and are beginning to propose a range of digital health monitoring technologies, which has direct implications for aging in place and remote health care monitoring.

2.5 Sensing Technologies to support In-Home Studies

Two approaches have emerged in the research community for studying behavior in a home setting. The first is building a living laboratory where a very rich set of sensors and infrastructure are available for study specific behavioral questions. The other is to create deployable versions of sensing technology so that researchers can study behavior in more natural and authentic settings. Much of the research on sensing platforms for the home has been around detecting the occurrence for activities of daily living (ADL).

Hirsch *et al.* examine the social and psychological factors that influence the design of elder care applications [50]. Among their findings is a concern that assistive technology may be rejected if it detracts from the aesthetics of the home, leads them to feel spied upon, or creates a feeling of embarrassment over the need for assistance. Beckmann *et al.* present a study of end-user sensor installation and reaction to sensors in the home [11]. They had end-users install vibration sensors, electricity usage sensors, motion detectors, cameras, and microphones. They found that end-users made a variety of errors, often due to the directional requirements of sensors or uncertainty over exactly where a sensor needs to be positioned. They also found many negative reactions to the intrusion of sensors into the living space, including objections to the potential for damage caused by the adhesive used for installation, concerns that sensors were placed in locations accessible by children or pets, and objections to the placement of cameras and microphones in the home. The also offer some design principles for deploying in-home sensors to end-users. By requiring only a few easy-to-install modules, the PowerLine Positioning approach greatly reduces these concerns.

Rowan and Mynatt installed strain sensors on the underside of the first floor of an elder's home to deploy their Digital Family Portrait application [112]. By detecting the weight of a person standing on the floor, these sensors allow the Digital Family Portrait to portray movement information in the home. The installation of these sensors is difficult and very time consuming because the installation required access to the underside of the floor, making it impossible to use these sensors on the second floor of an existing home.

Tapia *et al.* discuss home activity recognition using many state change sensors, primarily contact switches [123]. These sensors were taped to surfaces in the home and logged activations of the sensor for the duration of a study. While the ability to install a contact switch nearly anywhere in the home might seem to provide more information than can be obtained from the IMS-based approach, most of the sensors in this research were installed in the kitchen or bathroom, with success in detecting activities such as meal preparation and toileting. Also developed by Tapia *et al.*, MITes (MIT environmental sensors) are low-cost, wireless devices for collecting real-time data of human activities in natural settings [124]. The system includes five wearable sensors: on body acceleration, heart rate, ultra-violet radiation exposure, RFID reader wristband, and location beacons.

Wilson and Atkeson examine tracking and activity recognition using motion detectors, pressure mats, break beam sensors, and contact switches [136]. This work is of interest because it tackles the problem of recognizing the activities of several people sharing a home. In contrast, most research assumes that a single person causes all sensor activations. While they are able to track the locations of multiple people in the home, their approach requires the installation of many sensors in the living space and activity recognition is currently limited to movement.

Philipose *et al.* present the use of an RFID-enabled glove to monitor activities of daily living [107]. A person wearing the glove interacts with RFID-tagged objects, and the system recognizes activities based on interactions with objects. Even if a person is generally willing to wear the reader, they may choose to remove it in situations where it may come into contact with water, as during bathroom use and meal preparation.

Many of the current sensing approaches aim to address particular behaviors and location is often implicitly inferred. For location-based studies, deploying many sensors in the home is not often efficient. The more sensors that are deployed, the higher the likelihood for failures and longer deployment times.

Similar in spirit to PowerLine Positioning, Fogarty *et al.* explore attaching simple microphones to a home's plumbing system to detect activity in the home [36]. The appeal of this solution is that it is low-cost and easy-to-install. ADT Security System's QuietCare is beginning to offer simple activity data within a home using motion detectors from the alarm system [3]. Although these approaches do not offer unique and high resolution identification, they are sufficient for applications where just the presence of activity is important.

2.6 Differentiating Between Activity Sensing Approaches

I distinguish between what I call distributed direct sensing and a newly described category, infrastructure mediated sensing, which I informally call "home bus snooping" by analogy to computer network snooping. Distributed direct sensing involves the installation of a new sensing infrastructure into the home. This sensing infrastructure directly senses the presence, motion, or activities of its residents through sensors that are physically located in each space where activity is occurring. Example systems include a new set of sensors and an associated sensor network (wired or wireless) to transfer the sensor data to a centralized monitoring system where sensor fusion and activity inference take place. In contrast, infrastructure mediated sensing leverages existing home infrastructure, such as the plumbing or electrical systems, to mediate the transduction of events. In these systems, infrastructure activity is used as a proxy for a human activity involving the infrastructure [100]. A primary goal of this second category of systems is to reduce economic, aesthetic, installation, and maintenance barriers to adoption by reducing the cost and complexity of deploying and maintaining the activity sensing infrastructure.

Most of the existing literature in human activity sensing in the home falls into the distributed direct sensing category. In the pervasive computing research context, commonly used sensors for detecting human activity in the home include high-fidelity sensors such as visible light and IR cameras [128, 138] or microphones [10], as well as low-fidelity sensors such as passive infrared (PIR) motion detectors [137] and floor weight sensors [92]. High-fidelity distributed direct sensing has a long history of use in activity detection and classification research, primarily focused on computer vision or machine learning systems that capture the movement of people in spaces [64]. For example, Chen *et al.* installed microphones in a bathroom to sense activities such as showering, toileting, and hand washing [15]. The use of these high fidelity sensors in certain spaces often raises concerns about the balance between value-added services and acceptable surveillance, particularly in home settings [11, 50]. Low-fidelity, distributed direct sensing work includes the use of a large collection of simple, low-cost sensors, such as motion detectors, pressure mats, break beam sensors, and contact switches, to determine activity and movement [123, 124, 136]. The principal advantages are lower per-sensor cost and reduced privacy concerns.

All distributed direct sensing approaches share the advantages and disadvantages of placing each sensor in close proximity to where human activity occurs. For example, commonly used cameras or PIR sensors require a clear line of sight to the desired room coverage area; the person being sensed will be able to see the camera or PIR sensor. Generally, cameras or PIR sensors are deployed in places that have adverse aesthetics, such as on walls, on ceilings, or above a door [16, 50]. The large number of sensors required for coverage of an entire building presents an inherent complexity hurdle. Installation and maintenance of (typically) tens of sensors in a home, or hundreds to thousands of sensors in a larger building such as a hotel, hospital, or assisted living facility, results in high labor costs during installation and an ongoing maintenance and sensor network management challenge during routine operation.

It is often difficult to balance the value of in-home sensing and the complexity of the sensing infrastructure. One example that illustrates this difficulty is the Digital Family Portrait system, a peace-of-mind application for communicating well-being information from an elderly person’s home to a remote caregiver [112]. In the system's deployment study, movement data was gathered from a collection of strain sensors attached to the underside of the first floor of an elder’s home. The installation of these sensors was difficult, time-consuming, and required direct access to the underside of the floor. Though the value of the application was proven, the complexity of the sensing limited the number of homes in which the system could be easily deployed.

Some recent innovative work in the infrastructure mediated sensing category leverages the existing infrastructure in a home to collect signals at a single location. A few researchers have recently begun exploring the use of existing home infrastructure to detect human originated events [36, 100, 101, 102]. A few microphones on the plumbing infrastructure in the basement of a home can infer basic activities, such as bathing or washing dishes, through acoustically-transduced signals [36]. A single plug-in sensor can classify events, such as the actuation of a light switch, through the analysis of noise, transduced along the power line, from the switching and operation of electrical devices [101]. These two approaches cover a complementary set of human activities, depending on whether a water- or power-related event precedes that activity.

Both of these approaches require human-initiated events, as identified through signals carried via the infrastructure of their corresponding resources, in order to provide human activity information. They ignore activities that do not include the use of the plumbing or electrical systems, such as movement and transitions between parts of the home. In the case of water event detection, there may be only a few water usage events per person per day, whereas with electrical event detection, there may be limited electrical actuations during the day when incoming sunlight illumination may result in reduced light switch use. This results in a relatively sparse activity dataset compared to a dataset obtained using a dense network of PIR motion sensors located throughout the home. Therefore, I was motivated to find an infrastructure mediated sensing technique that delivers movement information.

I contrast infrastructure mediated sensing with a "piggybacking" approach that simply reuses an existing sensing infrastructure in the home that may be present for other purposes. For example, ADT Security System's QuietCare [3] offers a peace-of-mind service that gathers activity data from the security system's PIR motion detectors. Although a promising approach, security motion sensors are only installed in a few locations in the home, primarily on the ground floors, resulting in a much sparser dataset than is needed for general activity recognition. However, one could imagine coupling a collection of IMS-based solutions to provide a general-purpose activity detector.

2.7 Studying Individuals with Mobility Disabilities

The Americans with Disabilities Act (ADA) [6] and, more recently, the New Freedom Initiative [85], have identified activity and participation as a societal goal for people with disabilities. In addition, the recently revised International Classification of Functioning, Disability and Health (ICF) identifies both activity and participation as key domains in rehabilitation research [134]. Increased activity and participation are thought by researchers to reflect increased community integration, greater independence and autonomy, less dependence on societal resources, and an overall increase of a sense of individual wellness. In addition, it is well established that people with mobility disabilities confront increased challenges to participation in daily activities [37]. Enabling increased participation was a major goal of the Americans with Disabilities Act (ADA), however, participation levels have failed to increase for people who use mobility devices, thus calling for more research in this area [89].

Wheelchair users comprise about one-quarter of mobility device users, and the prevalence of wheelchair use has doubled in the last decade and is growing rapidly [69]. Wheelchair users are more likely to be limited in everyday activities than other mobility device users. More than 90% of wheelchair users report activity limitations and only 14.7% are able to complete all of the activities of daily living (ADL) tasks [59].

Research in the area of studying people that use ambulatory aids and wheelchairs has been fairly limited. Most information about people's daily activities is collected through self-report measures, such as diaries and surveys. While these are valuable techniques, they have limitations [117]. At a recent conference on mobility disability (Mobility RERC Conference [82]), the general consensus among the community was that what is needed is a methodology that imposes minimal burden on subjects while systematically gathering factual data on the daily movements and activities of people with disabilities who use wheelchairs and other mobility devices.

Studies of wheelchair mobility have been focused primarily on technical requirements for accessibility, such as ramp slope and surface materials [114]. As a result, a growing body of research has begun to focus on identifying barriers to outdoor mobility, such as distance traveled, level changes, and width of walkways [39].

Barriers to participation result from diverse factors, both intrinsic and extrinsic to the individual. The past decade has seen the development of numerous self-report instruments measuring participation and activity in various disability populations [37, 40, 60, 77, 78]. Some aim to reflect normative values of society and others employ a subjective, person-perceived approach. In addition, most measures are directed towards a general disability population and query participation in terms of commonly performed activities (such as ADL). Few measures exist that were developed exclusively for people with mobility disabilities. Some examples that do are PARTS/M and FABS/M [40]. PARTS/M queries activities in terms of destinations and considers the role of assistive technology as it facilitates or hinders participation. However, its length as a self-report instrument presents a significant challenge to both subject and researcher. Keysor *et al.* have developed a self-report measure designed to characterize factors in a person's home and community that may influence their level of participation [60]. Similarly, the Craig Hospital Inventory of Environmental Factors (CHIEF) is an instrument designed to access the user's perceived impact of environmental factors [134]. The Home Accessibility Survey (HAS) is another example (see Appendix A)

Meyers *et al.* present currently one of the few studies that tries to document environmental barriers among wheelchair users [78]. Their focus was on outdoor destinations and determining the barriers in their way. The investigators conducted 28 daily phone call interviews about their day. The participants were asked to recall their mobility patterns for that day and elaborate on any environmental incidents that either hindered or helped in their task.

Shaumway-Cook *et al.* present an approach where researchers observe and video record certain structured community mobility activities, such as going to the grocery store or seeing a physician [120]. After coding the video, researchers were able to later go back and note when the participants encountered environmental barriers. Although this approach provides rich objective data, it requires a very time-consuming and expensive video coding process. Thus, it is impractical for large-scale studies.

Monitoring people's daily activities through passive sensor-based techniques can be used to overcome many limitations of self-report measures. For example, accelerometer-based physical activity monitors have been demonstrated to record accurate levels of physical activity over long periods of time for ambulatory populations [132]. Others have measured the average speed, distance, and frequency of wheelchair users [24]. Global positioning systems (GPS) have been used in transportation and travel studies, and its potential to capture mobility outdoor activities of people with disabilities who rely on wheelchairs and other mobility aids have also been explored at Georgia Tech [68, 122]. By having this data at hand prior to the interview, it is no longer necessary to ask subjects to estimate the frequency of past activities. Rather, the time saved can be focused more extensively on the participatory and environmental context of activities.

Researchers have also explored using motion planning algorithms to predict whether a building has accessible routers for wheelchair use [42]. An easy way to collect location information is important to facilitate this kind of work where researchers want to collect enough quantitative data about mobility habits to apply route planning or other machine learning techniques.

2.8 Studying Mobile Phone Users

The mobile phone, initially a device simply for strategic communications, has gone through a long evolutionary process. Originally, the phone was designed primarily for durability. In the 1980's, this trend shifted, and mobile phones moved into the consumer product space where style, looks, and usability become more important. Now, they come in a wide variety of form factors with numerous possible combinations of services. During this evolution, people have been studying mobile phone usage patterns. Marketing firms and mobile phone manufacturers study a variety of user needs, from the calling plans that are most appealing to certain demographics to the usability of the handset itself.

Much of this research has focused on the design of new handsets and/or new services. For example, in 1998, Vaananen-Vainio-Mattila and Ruuska presented an ethnographic study of mobile phone users conducted at Nokia [127]. In this study, the authors used contextual inquiry to uncover both the sociological and cultural considerations affecting mobile phone usage and the design challenges and some potential basic solutions for the handset itself. Palen *et al*. took a slightly different approach, focusing on the use of the mobile phone system, including everything from the sales people to the phone itself to the service contacts [96]. Schlosser investigated the ways in which mobile phones are appropriated into organizations and daily activities [116]. She used interviews to uncover both these details and, in turn, how those individuals, organizations, and activities change based on this use.

This related research shows the power and the limitations of these types of studies with real mobile phone users. Palen and Salzman [95] note that although direct, naturalistic observation can help investigators to understand interactions as they "really happen… tracking particular participants requires getting access to the many places participants spend their time while also involving a large time commitment for all parties." Thus, they chose to supplement interviews not with observation but with voice mail diary entries, in which mobile phone users called a voice mailbox daily to report their interactions and troubles. McGuigan explores how social science methods can and should be used to study mobile phone usage, describing in depth the strengths and weaknesses of four different sociological methods: social demography; political economy; conversation, discourse, and text analysis; and ethnography [76].

Automatic logging, in which software automatically records the user's actions for later analysis, provides many of the benefits of observation methods without some of the problems. Researchers can gather data across all times, locations, and activities without being excessively intrusive to the participant. For example, Demumieux and Losquin developed a tool that collects logs of applications used on mobile devices, including both mobile phones and PDAs [29]. Grinter and Eldridge used automatic logging of text messages coupled with group discussion to uncover text messaging habits among teenagers [41].

MIT's Reality Mining Project has used Bluetooth proximity and phone context to study mobile phone usage and predict things such as daily routine and social interactions, but has not yet explored proximity of a user to their mobile devices [30]. The Reality Mining project is one of the largest mobile phone experiments in academia. By the end of their experiment, they will have collected a dataset of over 500,000 hours of continuous data on daily human behavior. Their experiment has involved the deployment of one hundred Nokia 6600 smart phones pre-installed with custom logging software as well as a version of the Context application from the University of Helsinki [109]. An effort like this can greatly benefit from proximity data in order to provide a complete picture of a person's relationship to their mobile phone.

Similarly, the Mobile Media Metadata system leverages mobile phone contextual information to assist users in annotating images on their camera-phones (digital camera equipped mobile phones) [28], whereas other systems use cellular identification to predict user routes and location [66] and develop context-aware contact lists [94].

CHAPTER 3

LOCALIZING PEOPLE AND OBJECTS IN THE HOME

As discussed in Chapter 2, indoor location systems abound, most of which can be deployed in a home. However, there are limitations to many of these technologies that do not always make them practical for the home. In this chapter, I discuss these limitations and present a new location technology called PowerLine Positioning that tries to address many of these issues.

3.1 Current Limitations and Challenges

Targeting location systems for the home presents several interesting challenges. One major challenge is cost. In a commercial setting, more resources are typically available for disposal, and thus a company can justify the investment based on added productivity and the reduction of other costs. On the other hand, the average homeowner would have difficulty justifying a high cost. Also, consider a researcher wanting to install location systems in various homes for a study. The cost of deploying a system in multiple homes simultaneously is much greater than a single, larger commercial building, such as an office building or a hospital, because parts of the infrastructure have to be replicated for each home being studied.

Deployment time and ease-of-use are other essential considerations. Investigators have limited time they can spend in a participant's home, thus the entire installation process must be as short as possible. In addition, technical expertise can also vary greatly, so an easy-to-use solution is always desirable. One way to address this challenge is to minimize the number of components used in the system. Studies have also shown that homeowners are concerned with the appearance of their home after adding any additional instrumentation [50], thus arguing again for minimized infrastructure.

Recent advances in indoor location systems leverage existing wireless communication infrastructure (*e.g.,* 802.11 and GSM) to provide a value-added location service. The major advantage of these approaches is that a consumer does not have to purchase any specialized equipment and can still benefit from location-aware computing. Leveraging public infrastructure has the advantage of greatly reducing the requirement for new infrastructure, but one major drawback is that users have very little control of the infrastructure itself. The performance of systems that rely on publicly accessible infrastructure (*e.g.,* 802.11 access points or GSM cellular towers) can vary drastically depending on the location of the home. Service providers adjust the operational parameters of WiFi access points and cellular towers with little warning. These changes require recalibration of the location system. An alternative is to introduce new infrastructure in the home by distributing many low-cost, short-range beacons. The time required for installation and the possible impact to home aesthetics, however, limit adoption.

3.2 PowerLine Positioning

Inspired by this strategy of leveraging existing infrastructure and recognizing that there are drawbacks to relying on public infrastructure or the deployment of many beacons, I was motivated to devise a solution for indoor localization that would work in nearly every household. With the significant insight being to use the residential power line as the signaling infrastructure, PowerLine Positioning is the first example of an affordable, whole-house indoor localization system that works in the vast majority of households, scales cost-effectively to support the tracking of multiple objects simultaneously, and does not require the installation of any new infrastructure. The solution requires the installation of two small, plug-in modules at the extreme ends of the home. These modules inject a mid-frequency, attenuated signal throughout the electrical system of the home. Simple receivers, or positioning tags, listen for these signals and wirelessly transmit their positioning readings back to the environment. PowerLine Positioning is capable of providing sub-room-level positioning for multiple regions of a room and has the ability to track multiple tags simultaneously.

3.2.1 Theory of Operation

In the PLP system, two signal generator modules are plugged into standard electrical outlets, and their respective signals emanate from those outlets to the rest of the home through the household power lines. One of the two modules is installed into an outlet close to the main electrical panel or circuit breaker and the other is plugged into an outlet that is located along the powerline infrastructure furthest from the first module (see Figure 2). In most cases, physical distance is a good estimate for electrical distance. In the case of a two-story house with a basement, for example, one module would be placed at the southwest end of the house in the basement (where the main panel is located) and the other in the northeast end on the second floor. Each module emits a different frequency tone through the power line. Both modules continually emit their respective signals over the power line, and portable tags equipped with specially tuned detectors sense these signals in the home and relay them wirelessly to a receiver in the home. Depending on the location of the portable tag, the detected signal levels provide a distinctive signature, or fingerprint, resulting from the density of electrical wiring present at the given location and the distance from the plug-in module.

A receiving base station in the home (*e.g.*, a wireless receiver connected to a PC) analyzes the fingerprint and maps the signal signature to its associated location based on a site survey. A site survey is conducted by having a user walk around with a location tag and manually identifying on a map their position.

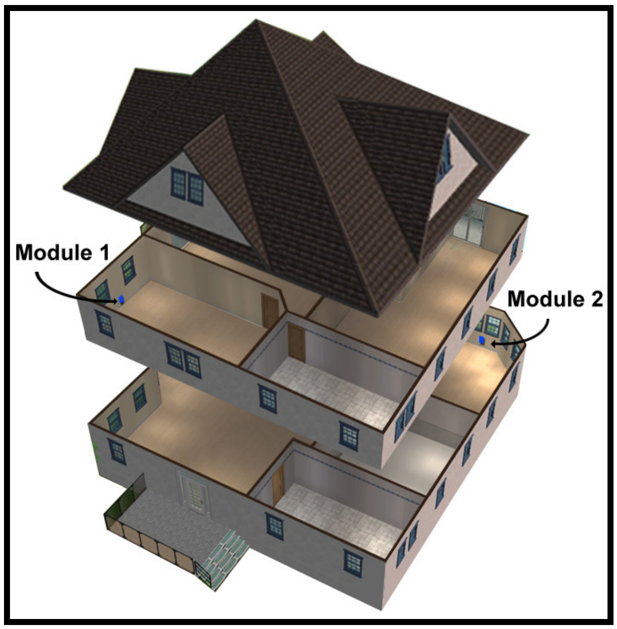


Figure 2: Placement of two signal-generating modules at extreme ends of a house

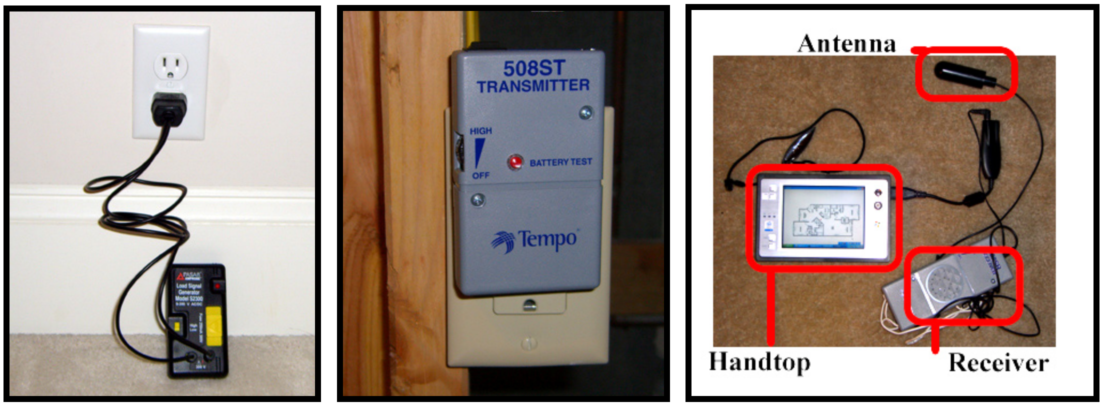


Figure 3: The PLP system components of initial proof-of-concept. The top shows two examples of off-the-shelf, plug-in tone generator modules. The bottom shows a working prototype of the location tag, consisting of a receiver and antenna hooked to a handtop computer for analysis.

When the modules are active, the tone detector or receiver tag detects the presence and amplitude of the attenuated signals throughout the home. The current implementation uses only the amplitude of the two signals, which has shown good results on its own. Because electrical wiring typically branches inside the walls, ceiling, and floors, signal will be present throughout much of the main living areas of the home. Some factors that contribute to the amplitude of the received signal at any given location:

- the distance between the receiver and electrical wiring,
- the density of electrical wiring in an area, and
- the length of electrical wiring from the modules to the receiver's location.

Figure 4 shows a signal map of a bedroom (left) and of a kitchen (right) from the same house. In the bedroom, the strength of both signals increases near the walls where there is the greatest concentration of electrical wiring and outlets. The strength of Signal A (left value in each cell of Figure 4) is weaker than the strength of Signal B (right value in each cell) in the kitchen, and the opposite is true for the bedroom. Because the two rooms are on different floors and at opposing ends of the house, each room is closer to a different module.

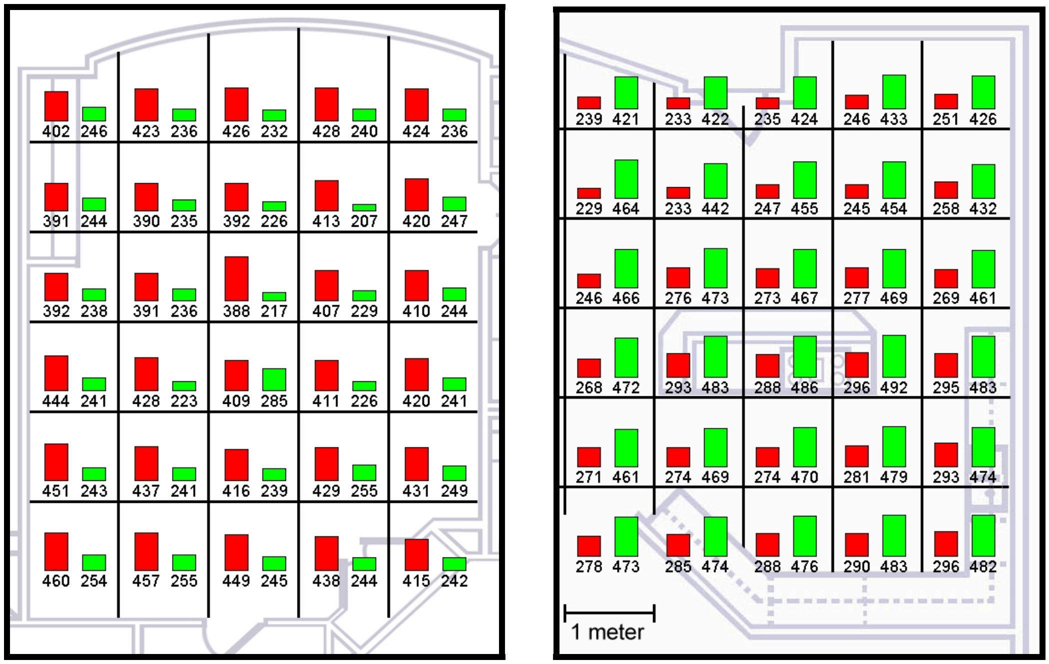


Figure 4: Left: Signal map of a bedroom. In each 1 meter cell, the left-hand number corresponds to signal strength from one tone generator and the right-hand number corresponds to the signal strength of the other tone generator. Right: A similar signal map of the kitchen in the same house.

3.2.2 Advantages of PowerLine Positioning

Almost every home in the U.S. has electrical power, and it is an assumed cost of the homeowner to maintain this infrastructure over the lifetime of the home. Thus, the infrastructure is already available and is usually well maintained. One key advantage of leveraging the powerline infrastructure is user control of the infrastructure. Users have very little control of the parameters of GSM cellular towers or a neighbor's WiFi access point, thus changes can happen unexpectedly. In contrast, users have control of the powerline infrastructure. Furthermore, there is stability in signal propagation over this infrastructure. Initial investigation shows that the cost and power requirements of the location tags favor that of the PLP system because of its simple sensing requirements, as opposed to the more sophisticated chipset associated with GSM and WiFi reception. In addition, the cost of the signal generating modules would also be cheaper than buying additional access points if one were investing in a location system for the home.

3.2.3 PowerLine Positioning Implementation

In this section, I discuss the various iterations of developing PLP. I also discuss the underlying theory behind the technology, the implementation details, and the performance evaluations.

3.2.3.1 Proof of Concept

For rapid development and investigation, I modified commercially available tone generators and tone detectors used by electricians for wire finding. This approach was valuable in quickly assessing the viability of this approach.

3.2.3.1.1 *Plug-in Signal Generator Module*

I used the Textron Tempo 508S and the Pasar Amprobe 2000 tone generator modules. These modules produce a 447 kHz and 33 kHz tone, respectively, on an energized 120 V AC powerline without causing any interference to household appliances. Additionally, the modules are powerful enough to transmit a tone up to 500 meters over the electrical wire (both hot and ground) and can be adjusted to emit at a lower signal strength. For the PLP prototype in this paper, I manually adjusted the signal strength depending on the size of the residence. I collected samples with the receiver near the module and samples near the opposite side of the home where the second module is located. I then tuned the signal strength such that I produced a large signal difference between the two locations without turning it down so much that the tone did not reach the far end. It was important to turn down the output level and use the middle of the receiver's dynamic range, because very high signal strengths would overwhelm the receiver and would not produce as large of a signal difference. Although I manually performed the steps described above, it is possible to build the modules to self-calibrate its output level during the installation and surveying steps. Based on the cost of the commercial wire-finder that inspired the PLP system, the cost for each module would be approximately US$50.

3.2.3.1.2 *Tag*

I modified a Textron Tempo 508R passive wideband tone detector to act as a prototype tag that would send sensed signals to a portable computer for analysis (see Figure 3 and Figure 6). The toner has a built-in frequency divider that maps a range of high frequency tones to audible sounds while still preserving the amplitude of the original signal. The receiver’s internal frequency divider translated the 447 kHz signal to about 1000 Hz and 33 kHz signal to about 80 Hz. I altered the tone detector to interface with the audio line-in jack of a portable computer to capture the signals. The tone detector also has an integrated omnidirectional antenna. I found the antenna worked best when held vertically (perpendicular to the ground). When placed in this position, the azimuth orientation did not affect the received signal levels.

For experiments reported, I used a rather large tag prototype that was easier for me to build. There are a variety of ways to construct a small and inexpensive version of this tag. One way is to feed the radio transducer or antenna through a series of op-amps and into a DsPIC microcontroller. A low-power Ming or Linx RF transmitter would transmit the readings back to a receiving computer. Alternatively, I could bypass the need for a microcontroller by using multiple tone decoder ICs, similar to the NE567 IC, which supports signal power output. Powered by a small lithium cell, the tag could easily be the size of a small key fob and run for a significant period of time using a mechanical motion switch. I believe the tags could be constructed at US$20 each, based on current retail hobbyist prices.

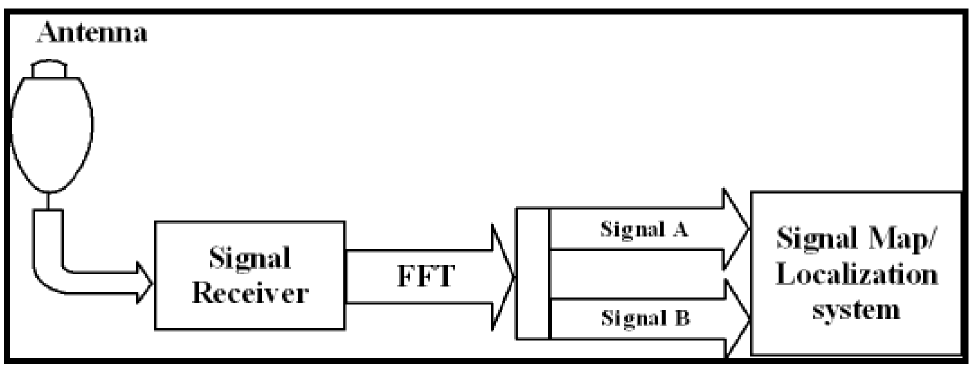


Figure 5: Block diagram of the overall tagging system of the PLP proof of concept.

3.2.3.1.3 *Software*

In the experimental set-up, I wrote an application in C++ to sample the signal from the sound card's line-in jack where the prototype receiver tag is connected. The application acquires 16-bit samples at a rate of up to 44 kHz and performs a Fast Fourier Transform (FFT) on the incoming signal to separate component frequencies for the analysis. The application performs this analysis in very close to real-time and makes the raw signal strengths for the two frequencies of interest (447 kHz and 33 kHz) available through a TCP connection for other parts of the PLP system to access.

A second application, written in Java, performs the machine learning and provides the user interface for the system (see Figure 6). The Java application connects to the FFT application and reads the raw signal values. The application provides the user interface for surveying the home and an interface that shows the current location after it has been calibrated. The Weka toolkit [133] allows for real-time programmatic execution of KNN queries to the location model. I also use Weka for *post hoc* analysis, such as cross-validating the model when determining optimal *k* values and performance testing.

The experimental prototype used for the empirical validation consisted of a Sony Vaio-U handheld computer with all software applications (signal receiver, learner, and the user interfaces) loaded and the receiver hardware connected (see Figures 1 and 6). Using this small but powerful device provided me with an easy method for surveying homes.

Figure 6: User interface used for mapping and localizing the position of the connected receiver.

3.2.3.2 Localization Algorithm

The PLP system relies on a fingerprinting technique for localization. Although this technique often provides more detailed and reliable data, it requires the generation of a signal topology via a manual site survey. The granularity of the survey dictates the final accuracy of the positioning system. For PLP in the home, the site survey is a one-time task provided the modules stay fixed and the electrical characteristics of the home remain the same.

Effective application of fingerprinting requires the signals to have low temporal variations, but high spatial variation. As discussed above, the propagation of signals transmitted via the powerline exhibits both of these properties, because the detected signals vary little unless the modules have been moved or the electrical system has been significantly remodeled. The use of two different signals and the variability in the electrical wire density throughout the homes provides this spatial variation. The localization algorithm used in PLP proceeds in two steps. The first step predicts the room, and the second predicts the sub-regions within that room. Both use *k*-Nearest Neighbor (KNN) classification.

3.2.3.2.1 *k-Nearest Neighbor (KNN) Classification*

The room and sub-room localizers use a *k*-Nearest Neighbor (KNN) [81] classification to determine the receiver's room location. KNN-is a memory-based model defined by a set of objects known as learned points, or samples, for which the outcomes are known. Each sample consists of a data case having a set of independent values labeled by a set of dependent outcomes. Given a new case of dependent values (the query point or unknown value), I estimate the outcome based on the KNN instances. KNN achieves this by finding *k* examples that are closest in distance to the query point. For KNN classification problems, as in this case, a majority vote determines the query point's class. For this task, given an unlabeled sample, χ, I find the *k* closest labeled room samples in the surveyed data and assign χ to the room that appears most frequently within the *k*-subset. For the distance measure *d*, I use the Euclidean distance,

$$d\ (x,y)=\sqrt{(\sum_{i=1}^{2}(x_i-y_i)^2)}\,,$$

in which tuples x = <Signal A_{x1}, Signal B_{x2}> and y = <Signal A_{y1}, Signal B_{y2}>. The tuple *x* refers to the labeled signal point and tuple *y* refers to the unlabeled query point sensed by the receiver tag. For more modules, I increase the dimension to match the number of modules.

3.2.3.2.2 *Room and Sub-Room Localization*

The key differences between the room and sub-room localizers are the labels assigned to the data points and the value for *k* used in the localization. For the room level classification, I assign room labels to samples from the site survey. In the sub-room classification, I further subdivide the same samples and assign sub-room labels to them. For each home, there is an optimal value of *k* for the room level localizer. Within the same home, there is an optimal value for the sub-room level localizer for each room. Thus, for localization, I first execute the KNN classification using the room labeled samples and its optimal *k* value. After determining the room, I execute KNN on the sub-room labeled samples from that room and its optimal *k* value to determine the sub-room.

3.2.3.2.3 *Training the System and Determining k in KNN*

The choice of k is essential in building the KNN model and strongly influences the quality of predictions, for both room-level and sub-room-level localization. For any given problem, a small value of k will lead to a large variance in predictions. Alternatively, setting k to a large value may lead to a skewed model. Thus, k should be set to a value large enough to minimize the probability of misclassification and small enough (with respect to the number of cases in the example sample) so that the k nearest points are close enough to the query point. Thus, an optimal value for k achieves the right balance between the bias and the variance of the model. KNN can provide an estimate of k using a cross-validation technique [81].

Splitting the localization into two steps can help control the cluster sizes. In localizing the room, I want to use a larger value of k so that I consider a larger region when trying to find where the unknown signal potentially maps. To localize within a room, I consider smaller values of k so that I match finer clusters and because of the smaller data sets within a room than the whole home.

The training interface allows end users to build a signal map of the home (see Figure 6). The user loads a pre-made or hand-drawn floor plan of the residence into the application. The interface displays the floor plan, and I physically travel to different locations in the home and choose the approximate location on the floor plan. When a location is selected, the application stores the fingerprint for that location, which is a one-second average of the two detected signals. The same process continues throughout different points in the home. Surveying at a granularity of approximately 2-3 meters in each room produces more than sufficient accuracy for the initial experimental test cases.

The interface allows the user to assign meaningful labels to different room and sub-room areas, such as “kitchen” and “center of master bedroom.”

For optimal performance in sub-room level localization, I typically segment each room into five regions: the center of the room and areas near the four walls of the room. The user is free to select the location granularity (assuming sufficient training sets) of their choice for important regions. However, the desired segmentation may not reflect the actual segmentation the underlying set of signals can provide. For example, a user may want to segment the middle part of a bedroom into four regions, but there might not be enough signal disparity among those regions for the KNN classifier to work well. I provide some assistance in overcoming those limitations by automatically clustering the room into potential sub-regions that are likely to be accurately classified based on the room’s signal map. I employ a k-means clustering algorithm [81] to provide graphical suggestions on where to segment for a desired number of sub-regions.

After the signal map has been constructed and all data has been labeled, the algorithm cross-validates model data to find suitable k values for the room and sub-room classifiers. Cross-validation involves the division of the data samples into a number of v folds (randomly drawn, disjoint sub-samples or segments). For a fixed value of k, I apply the KNN model on each fold and evaluate the average error. The system repeats these steps for various k values. The system selects the value for k achieving the lowest error (or the highest classification accuracy) as the optimal value for k. This value for k depends on the home and the number of sample points. Generally, I see optimal k values near 10 for the room localizer and k values near 3-5 for the sub-room localizer.

3.2.3.3 Proof of Concept Performance Evaluation

I evaluated the performance of the PLP system in 8 different homes of varying styles, age, sizes, and locations within the same metropolitan city. The evaluation also included new homes and older homes, both with and without remodeled and updated electrical systems (see Table 3 for specifications of the homes). In addition to evaluating the system, I simultaneously conducted infrastructure tests of WiFi and GSM availability to provide some comparison with other indoor localization results. The infrastructure tests only involved logging the availability of wireless 802.11 access points and multiple GSM towers in the home.

In each home analyzed, I first installed the PLP system, calibrated the two tone modules, and created a signal map by surveying the whole home. When creating the signal map, I took at least two signal readings every 2-3 meters throughout the home to ensure I gathered enough training and test data (Table 4 shows the number of sample points for each home). Each reading was taken for 3 seconds with an individual holding the receiver in hand (about 1.5 meters from the ground). After creating the signal map, I used the interface on the handheld to assign the appropriate room and sub-room labels to the data.

I calculated the classification accuracy of the room and sub-room predictors. The sub-room accuracy was calculated independent of the room-level predictor. Three meter regions were used for the sub-room-level tests. After testing each room, I averaged all the sub-room localization accuracies to produce a single sub-room level accuracy value for each home.

Table 3: Details of the home where the PLP system was deployed and evaluated

Home	Year Built	Electrical Remodel Year	Floors/ Total Size (Sq Ft)/ (Sq M)	Style	Bedrooms/ Bathrooms/ Total Rms.	Population Density
1	2003	2003	3/4000/371	1 Family House	4/4/13	Suburb
2	2001	2001	3/5000/464	1 Family House	5/5/17	Suburb
3	1992	1992	1/1300/120	2 Bed Apartment	2/2/6	Downtown
4	2002	2002	3/2600/241	1 Family House	3/3/12	Suburb
5	1967	2001	2/2600/241	1 Family House	3/3/11	Suburb
6	1950	1970	1/1000/93	1 Family House	2/2/5	Suburb
7	1926	1990	1/800/74	1 Bed Loft	1/1/5	Downtown
8	1935	1991	1/1100/102	1 Family House	2/1/7	Suburb

Table 4 shows the results of the PLP room-level and sub-room level accuracies for various homes. Room accuracy ranged between 78–100% and sub-room accuracy ranged between 87–95%. The modern homes and the older homes with updated electrical infrastructure resulted in similar performance results. The updated electrical systems in these homes were accompanied with an overall remodel of the home, which tends to include the addition of electrical outlets and lighting. The single family home that exhibited a significantly lower accuracy (Home 8) was an older home with an updated electrical system. However, that home had a two-phase electrical system, which I only learned after installing the PLP system. Because it is a smaller house and Phase 1 drives a small number of outlets, I simply placed the modules on Phase 2 to produce acceptable (though not optimal) coverage throughout the house. However, installing a simple phase coupler would have improved its performance.

The condominium and apartment test cases also produced promising results. The condominium was converted from an office building, but the electrical system was completely remodeled to a residential style system. Although one wall of the condominium used a metal conduit to run its electrical wire, PLP still worked because the room with the conduit was small and the receiver was never too far from the wall. The apartment also featured a similar residential style electrical system. Because of the small size of the living spaces, I had to turn down the power of the modules significantly in the two cases, unlike the larger homes I tested.

The older homes without an updated electrical system exhibited lower results for two reasons. First, these homes lack a proper electrical ground, resulting in one less path for the signal to propagate, because I send the signal both on the hot and ground wires. Homes with an updated electrical system have an extra electrical ground wire running through the home, which is usually grounded to the copper water pipes. This grounding enables additional signal propagations to certain areas of the home. Second, these homes tended to have fewer electrical outlets than the modern or remodeled ones, resulting in poor detection in some areas.

Table 4: Accuracy results by home. For each home, I report the accuracy of room-level prediction and the average sub-room-level prediction across all rooms (Note the room-level and sub-room accuracy values are independent of each other). The sub-room-level regions were defined to be up to approximately a 3 square meters. The WiFi and GSM measurements indicate the maximum number of access points or towers seen at all times during the surveying and the total number of unique access points or towers seen during the whole surveying period.

Home	Size Sq Ft/ Sq M	Sample points	Rooms surveyed	Room Accuracy	Sub-Room Accuracy at 3 M	WiFi Always/ Max	GSM Always/ Max
1	4000/371	194	13	89%	92%	3/12	3/5
2	5000/464	206	15	95%	93%	1/3	2/4
3	1300/120	95	6	90%	90%	3/7	4/12
4	2600/241	183	11	88%	87%	1/3	3/5
5	2600/241	192	10	92%	93%	2/4	3/6
6	1000/93	76	5	100%	94%	0/2	4/6
7	800/74	65	5	93%	95%	2/11	3/9
8	1100/102	80	7	78%	88%	2/6	3/7

3.2.3.3.1 *Understanding Classification Errors*

To understand the types of classification errors encountered by the PLP system, I analyzed the confusion matrices for each home. For some homes, most of the classification errors resulted from misclassifying rooms as one of the adjacent rooms. The adjacency errors appeared when trying to localize very near the boundary or the wall of a room. These errors were more prevalent in larger houses near common walls between two adjacent rooms of similar size. Open spaces that were divided into multiple rooms also resulted in errors. Other homes, however, exhibited more random classification errors possibly due to errors in the survey map, sparse sampling, or in error readings coming from the receiver at that time. One possible solution to guard against misclassifications is to use hysteresis to compare against certain classifications and see if those classifications follow a valid trail. Some homes could benefit from hysteresis, especially those with significant random error (see Figure 7).

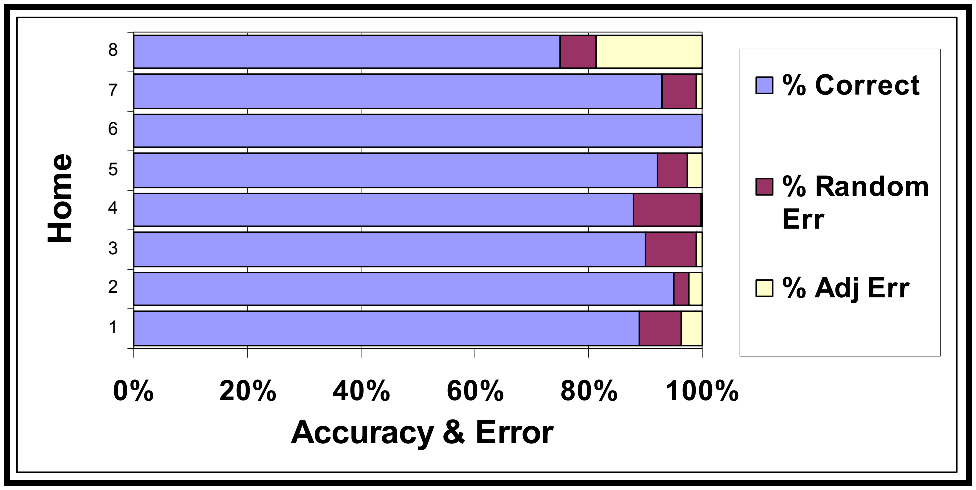


Figure 7: This figure shows the percentage of incorrect room predictions identifying a room that is adjacent to the correct room.

3.2.3.3.2 *Number of Modules and Performance*

I conducted accuracy tests using a varying number of modules. Although the goal was to minimize the additional hardware the user must install in a home, there might be cases in which higher accuracy is more desirable. Adding additional modules is the main way to increase overall accuracy. Figure 8 shows both room-level and sub-room level accuracies for an increasing number of modules for a particular home as an example. Additional modules do increase the accuracy for both predictions, but there is a point of diminishing returns. For this home (Home 1), two or three modules are the best number. I observed similar trends in other homes I tested and generally, two modules were sufficient.

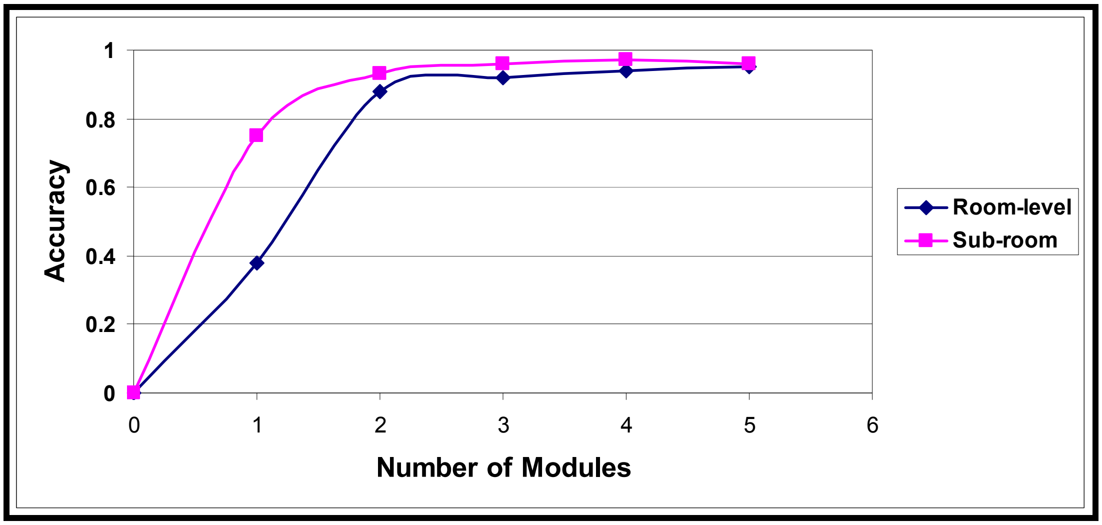


Figure 8: The effect of number of modules on room-level and sub-room-level classification accuracies. Tests were conducted on Home 1.

3.2.3.3.3 *Resolution Analysis*

In the initial evaluation, I sub-divided rooms into approximately 3 meter regions. This resolution yielded high accuracies around 90%. Higher resolution, or smaller subdivisions of each room, is possible, but at the cost of accuracy. In addition, higher resolution also requires dense mapping of an area. To investigate the specific accuracy to resolution tradeoff, I performed a fine-grain survey (sampling down to every 0.5 meter for a total of 96 samples) of a room (6m X 6m) in Home 1. With the current implementation, the lowest obtainable practical resolution is 1 meter. The accuracy falls below 70% for 1 meter regions (see Table 5), because there is a theoretical limit to the detectable differences between small movements in the space and the signal amplitude. However, finer granularity may be possible by considering the phase difference between the two signals. From my observation, the maximum amplitude differential is about 20 units when moved 1 meter for a modern home using this system. However, I will show how sub 1-meter resolution can be obtained using just SNR with a new hardware design.

Table 5: **The sub-room-level accuracies for smaller sub-regions for a particular room in Home 1. A total of 96 points were surveyed.**

Sub-room region size	4 m	3 m	2 m	1 m	0.5 m
% Accuracy	94%	91%	74%	67%	42%

3.2.3.3.4 *Temporal Signal Stability*

Fingerprinting works best with a signal that is time-independent but spatially diverse. The data presented so far only considered results over relatively short periods of time, usually around 1 hour worth of data collected at a particular home. To test the stability of the signals over time, I conducted two separate tests. First, in Home 1, I conducted separate surveys over the course of several weeks. I trained the system on data from one survey and checked its accuracy against data collected from different surveys. Room prediction was correct 88% of the time (compared with the value of 89% for Home 1 in Table 4) and sub-room level prediction was correct 89% of the time (compared with the value of 90% in Table 4). Second, in Home 2, I collected 45 hours of data over a three-day period (Saturday through Monday) in a single location (the kitchen). The kitchen was an interesting test because it contained a large number of features that could affect the tone signals (*e.g.,* plentiful overhead lighting, appliances being turned on and off throughout the day, talking on a cordless phone, people gathering around the tag). Figure 9 depicts the stability of the signal for four different 3-hour intervals. The results suggest there is deviation (17 units on average), but it is not significant enough over the full dynamic range to cause major classification errors.

Modifications to the electrical infrastructure can contribute to accuracy errors and require recalibration, which was a problem I noted for other infrastructure solutions

(802.11 and GSM). However, most situations, such as turning on a light switch, only energize a portion of the electrical line and do not affect significantly the accuracy in my experience. More studies are needed to empirically study this. Construction of a “day” and “night” map using a richer data set can allay some of these concerns. The addition of an extension cord does impact the accuracy, depending on location and length. For example, running an extension cord in a bedroom after a site survey causes localization errors near the new cord, but not in other parts of the house. Thus, the problem is more local than global in nature. Dead reckoning or hysteresis-based algorithms can mitigate much of these problems. During the original experiments, I found that additional wiring such as extension cords tended to cause significant deviations in the received signal at about 1-meter from the cord. Another problem that I observed was the introduction of large new appliances with grounds. They exhibited similar characteristics as the extension, which the localization errors occurring at 1 meter from the devices.

PLP could be designed to recognize potential changes in the infrastructure from past data to notify the user that re-surveying of a particular area is necessary. Although I did not observe any problems with electrical interference with the continuous logging, during the site tests I did often observe electrical interference caused by home electronics and appliances, such as computers, televisions, and stereos. When I held the receiver next to some of these electronic devices, its broadband electrical noise often overwhelmed the receiver and caused spurious readings. This problem only existed when the receiver was very close (within a few centimeters) from such devices. To guard against learning or localizing incorrect fingerprints, one solution is to look for these signal interferences and filter out those readings, indicated by a clear broadband signature, before using the data in analysis. Table 6 summaries the sources of problems for PLP in the home I encountered during the deployments.

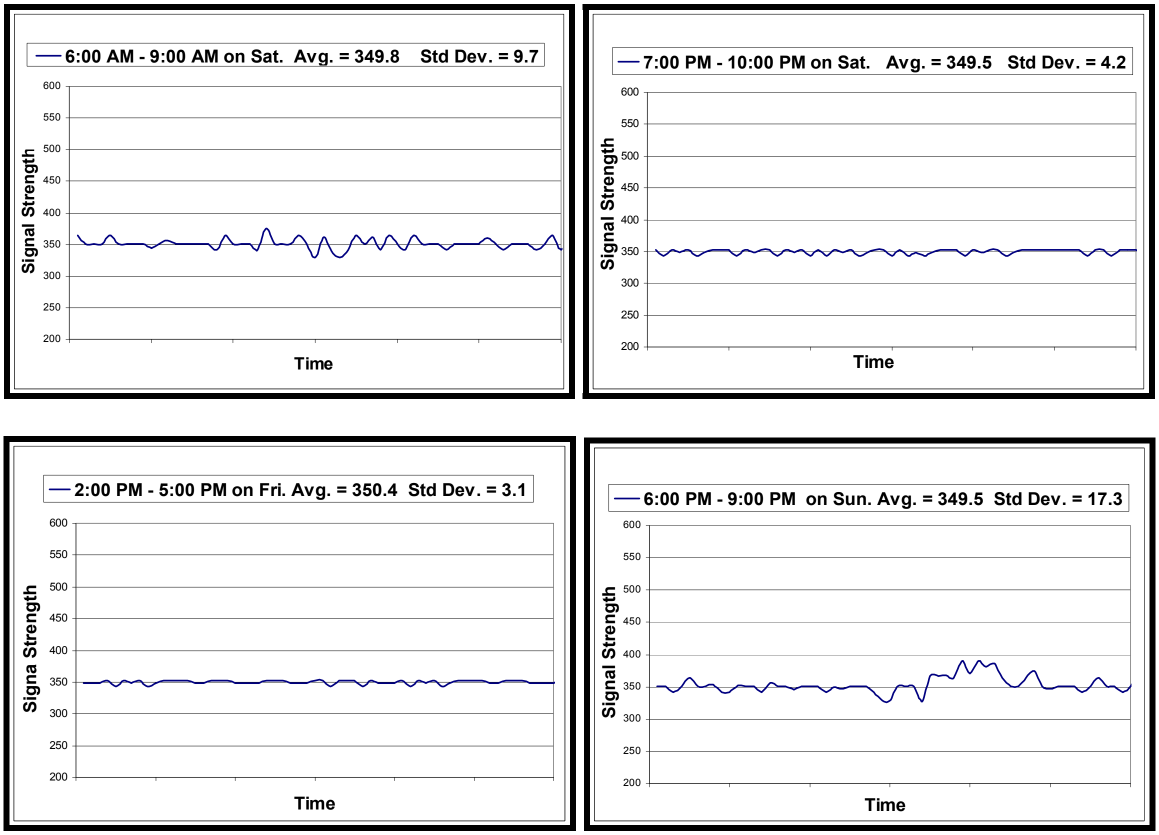


Figure 9: Temporal signal stability in the kitchen area of Home 2. The graphs show the signal values for the two toner modules (combined using the Euclidean distance) over various intervals during four days of continuous recording. The average signal values and the standard deviations are shown above each graph. The full dynamic range of the vertical axis is 0-1000.

Table 6: Summary of problems which cause localization error in PLP.

Problem	Area of space effected	Recalibration required?	Transient problem?	Potential solution
Consumer electronics devices	< 5 cm	N	Y	Broadband filtering on location tag
Grounded appliances	1-meter around appliance	N	N	Detect in software
Extension cords	1-meter near cord	N	N	Detect in software
High noise switching device (ex. microwaves)	Whole house	N	Y	Install noise filters or increase transmit power
Removal of 220V appliance	Whole house	Y	N	Installation of fixed 220V phase coupler device
Ham radio equipment	Whole house	N	Y	Dynamic frequency hopping support for PLP or using a wideband signal

3.2.3.4 Deployable Version of PowerLine Positioning

The second version of PLP consists of a self-contained wireless tag, which is suitable for deployment studies and evaluations. Appendix B includes the detailed specifications as well as the schematics and parts lists of both the tags and the plug-in modules.

The PLP tags and plug-in modules are tuned for two mid frequency (500 kHz and 600 kHz) AM modulated signals. These frequencies were chosen for two important reasons. First, I had to stay within the FCC Part 15 regulations and second, tuned components are readily available at these frequencies, which reduces the overall cost of the system. The tags are designed to extract the amplitude (signal strength) for each and wirelessly transmit back those two values along with a unique ID through an on-board RF transmitter to a base station connected to a personal computer. Two versions of these tags were developed. One used a Zigbee and the other used a Bluetooth backchannel. Minimally, the tags detect and transmit the signal values every 100 ms (10 Hz) at 10 bit resolution. The wireless backchannel has a range of up to 50 ft indoors. Future versions of this system will incorporate reflecting the data back over the powerline infrastructure, thus eliminating the need for any type of wireless backchannel.

Each data transmission unit from the tag consists of a 16 bit unique ID, two 10-bit signal values, and a single bit indicating if the button on the tag is pressed. The RF receiver connected to the personal computer is able to able receive data from up to 25 tags (base station limitation). An application running on the personal computer receives and parses the data, handles the fingerprinting algorithm, and provides location services to other applications.

The tag has an on/off switch and a single position push button. The button is used to indicate a special action to the remote computer. Currently, the intended uses are to tell the personal computer to store the current values to the fingerprint database during the calibration process and for people to indicate some event when carrying the tags. The tags also incorporate motion detection, so the tag will go into a standby mode if no motion is present for 30 seconds and reactivate itself on the next motion event. This approach greatly reduces the overall power consumption of the tag. With the tag duty cycling at 40% of the time, my experiments showed the tag would last about 4 weeks using a 750 mAh (3.6 V) alkaline or lithium-ion battery source.

After building the new version of the system, I conducted experiments similar to that of the proof-of-concept system to validate the performance of the new system. Table 7 and Figure 10 show the performance results of the new system deployed in 8 different homes. The redesign of the system greatly contributed to both the improved accuracy and resolution of PLP. This is attributed to two things. The first is the multi-staged tuned received tag design (see Appendix B), and the second is the use of different power line transmission frequencies (500 kHz and 600 kHZ).

Table 7: Accuracy results for another set of homes using the new design and deployable version of PLP. For each home, I report the accuracy of room-level prediction and the average sub-room-level prediction across all rooms at 1 meter.

Home	Size Sq Ft/ Sq M	Rooms surveyed	Room Accuracy	Sub-Room Accuracy at 1 M
1	4000/371	13	92%	84%
2	5000/464	15	96%	88%
3	1300/120	6	94%	90%
4	2600/241	11	88%	80%
5	1100/102	6	92%	92%
6	1600/149	6	96%	94%
7	1800/67	7	90%	86%
8	2400/223	8	98%	83%

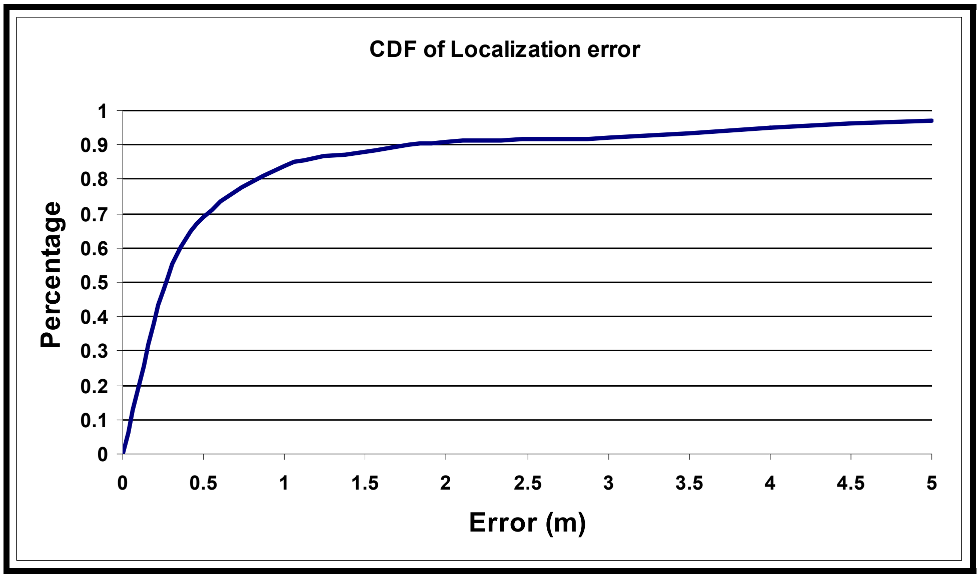


Figure 10: Cumulative distribution function (CDF) of the localization error of the deployment version of PLP. The results are aggregated across all homes where PLP was deployed.

3.2.4 Variations in the Powerline Infrastructure

In the United States, modern homes now follow a strict electrical code called the National Electronic Code (NEC). Electrical codes only became widely enforced in the 1980s, although many homes before that already followed similar guidelines. Although the specific regulations may change depending on state and city ordinances, each follows the same general requirements. These regulations ensure the electrical systems are consistent across homes of different sizes and styles. Specifically, the requirements outlined in the NEC favor the infrastructure requirements needed for the PLP system to work in modern homes. These requirements include regulations for certain “homerun” circuits through the house, a minimum number of outlets in a given space, and minimum lighting requirements throughout the house. These requirements serve as general guidelines on the kind of electrical infrastructure to expect in the home. Although PLP already performed reasonably well in older homes, it consistently achieved very good results in the new or remodeled homes that follow these requirements.

I specifically developed PLP to provide an affordable location system for home environments. However, commercial buildings must comply with strict electrical codes for which the PLP design must be altered to support. First, commercial wiring typically uses a two or three phase electrical system that prevents the signals from propagating throughout the entire electrical system. It is possible to overcome this problem by installing an inexpensive phase coupler that allows only the PLP signals to propagate between phases. Second, most commercial electrical wiring runs through a metal conduit, which blocks significant portions of the tone emanating from the wire (PVC conduits do not cause a problem). One solution to this problem is to increase greatly the signal strength and the other is to send the signal through both the electrical wiring and the metallic conduit itself. This problem also applies to homes that have been converted from commercial buildings without remodeling the electrical system.

3.2.5 PowerLine Positioning Discussion

The cost of infrastructure for WiFi is distributed across a community and assuming dense enough living conditions, it is a reasonable expectation that a single residence will be able to access other WiFi access points nearby. This is less likely in sparser housing, in which case users would be required to purchase multiple WiFi access points. Various cellular telephony service providers cover the cost of the infrastructure for GSM. The coverage is fairly dense in most metropolitan areas and will only get better over time. However, coverage is still fairly sparse in rural settings and many homes do not get very good cellular service in some rooms (see Table 4). Almost every home in the

U.S. has electrical power, and it is an assumed cost of the homeowner to maintain this infrastructure over the lifetime of the home. Thus, the infrastructure is already available and usually well maintained.

One key advantage of leveraging the powerline infrastructure is user control of the infrastructure. Users have very little control of the parameters of GSM cellular towers or a neighbor's WiFi access point, thus changes can happen unexpectedly. In contrast, users have control of the powerline infrastructure. Furthermore, there is stability in signal propagation over this infrastructure.

The cost and power requirements of the location tags favor that of the PLP system because of its simple sensing requirements, as opposed to the more sophisticated chipset associated with GSM and WiFi reception. In addition, the cost of the tone generating modules would also be cheaper than buying additional access points if one were investing in a location system for the home.

The significant advantage of PLP when compared against two popular fingerprinting techniques using WiFi/802.11 [8, 32] and GSM [93] lies in the better resolution, control of the infrastructure, and power requirements (see Table 8). However, PLP is not without its own challenges (see Table 6), but the control over the infrastructure helps mitigate some of those challenges.

Table 8: An overall comparison of PLP against two popular location systems that also use fingerprinting.

	PLP	GSM	WiFi
Output Type	symbolic	symbolic	symbolic (geometric using triangulation)
Resolution and Accuracy	3 m – 93% 1 m – 86%	20 m – 90% 2-5 m – 50% [93]	6 m – 90% 2-3 m – 50 % [8, 32]
Infrastructure Requirements.	2 plug-in signal modules	Located within GSM cellular service range	3 – 4 WiFi access points
Infrastructure Control	Full	None	Partial (dependent on ownership of access points)
Cost	US$20 for tag and US$50 per module	US$25 for tag	US$25 for tag and US$50 per access point
Spectral Requirements	10 kHz – 600 kHz	900 MHz and 1800 MHz	2.4 GHz
Update Rate	> 20 Hz	> 20 Hz	> 20 Hz
Tag power Req.	~50 mA (Pic + op-amp + antenna)	~200 mA (GSM receiver module)	~100 mA (microcontroller operated WiFi detector)
Simultaneous Tracking	Theoretically no limit	Theoretically no limit	Theoretically no limit

3.3 Deployment Study – Studying Wheelchair Mobility Users in the Home

Increased activity and participation for people with disabilities is a goal of the Americans with Disabilities Act (ADA) [6] and the New Freedom Initiative [85]. The aim is to reduce environmental barriers and increase access to assistive technologies in order to increase the ability of people with disabilities to integrate into the community, have a greater sense of autonomy, and lower dependence on societal resources. In addition, the recently revised International Classification of Functioning, Disability and Health (ICF) recognizes activity and participation as two of its four key components [134]. The ICF is a taxonomy that tries to represent all variables that may impact an individual's experience with disabilities. This is an important resource for healthcare providers because it provides a common language among healthcare professionals across the world. Information derived through the classification framework improves the understanding of health disparities between people with and without disabilities, among different regions, and through time. In addition, this can facilitate developing interventions towards preventing secondary conditions and mitigating environmental and societal barriers. The ICF has a broad range of different applications, such as social security, policy formation, evaluation in managed health care, and population surveys at local and national levels.

One particular area of interest is studying how environmental and personal barriers affect the well-being and health of people with mobility disabilities. People with mobility disabilities include those that require a full mobility aid, such as a manual or powered wheelchair, and individuals that require an ambulatory device, such as a walker or cane. The prevalence of wheelchair use has doubled in the last decade and is growing at a fast pace. In addition, studies show that more than 90% of wheelchair users report activity limitations and only 15% are able to complete all of their activities of daily living (ADL) mobility tasks. Thus, there is a strong motivation to study this population.

The assumption for this population is that wheelchairs are necessary for mobility, and mobility is the means to performing activities and community participation. However, in order to dress, eat, or bathe in a wheelchair, the home environment needs to be accessible (*e.g.,* wide enough doorways, wheelable ground surfaces, *etc*.). Studying and understanding the mobility patterns of wheelchair users in their homes can provide useful insights on where environmental barriers exist, how better to design assistive technologies, and how to improve the architecture of homes and offices. However, collecting this data is a difficult task.

New technological methods are needed to understand activity and participation in the everyday lives of wheelchairs users, especially in the home. The development of objective indoor measures is critical to understanding how people use mobility devices in the home and can be used to document where, when, and how people are using these devices. Additionally, it can help understand how specific environments in the home can facilitate or hinder a person's use of a particular device or the performance of a specific activity. In the disability research community, current measurement of indoor activities among wheelchair users in the home has been limited to self-report questionnaires, such as the Home Accessibility Survey (see Appendix A). Disability researchers have also used diaries to gather mobility problems when they occur. However, researchers have found that many incidents are missed with both of these methods. Participants also often forget to record an incident or do not realize that a particular situation is important. It is difficult with current practices to gather objective data, such as frequency and duration. A tracking system can automatically gather this information, while allowing the interview process to focus more on details of particular activities. Although the community has looked at automatically collecting this data, no indoor solution has been adopted because of current limitations in cost, deployment times, and additional infrastructure requirements.

Thus, the overall aim of this deployment study is to answer the following thesis claims:

- Is PowerLine Positioning easy-to-deploy, and what is the typical deployment time for a standard home?
- Can PowerLine Positioning provide objective, empirical data for location-based studies in the home?
- Does using automatically-sensed location and mobility data facilitate a richer interview process that produces better quality data?

3.3.1 The Value of Having Indoor Tracking

Indoor tracking technology can provide simple and automatic data about the activity and participation of individuals in a space. This information can serve as objective data against which researchers can probe for more detailed and targeted questions about device use and activity. Without the objective data from the location system, it then becomes possible that certain important incidents are forgotten through self-report.

Below, I present some the types of questions that mobility disability researchers are interesting in gathering about wheelchair users. The questions are based on current literature in the area. For each question, I briefly highlight how automatic location tracking can play an important role alone and when used in a mixed-method interview process.

- Where do people go to perform what activity?

    - The location data can show where people tend to spend a lot of time, and the interview can probe the participants about what activity what going on at those times.

- How do people who use mobility devices make use of spaces in the home, and how does it differ from non-disabled family members?
    - The location data can show traces of where disabled and non-disabled members of the family tend to go.

- What mobility devices do people use for a particular activity (*e.g.,* walker to enter the bathroom, shower chair in the bath, and wheelchair in the hallway)?
    - Tagging all the mobility devices will give information about which mobility aids are used in which parts for the home. Participants can be queried about particular situations to determine the reason for the transition.

- What is the frequency and duration of mobility device use in each room?
    - The location data can provide this information automatically and often more accurately than self-report.

- What routes do individuals take throughout the home? How have people adapted their homes (or not) and how does that impact mobility device use?

    - The location data can be aggregated to show time varying route information for each individual. The interview process can potentially reveal why certain routes are taken, such as a result of an environmental barrier.

- What parts of the home are completely inaccessible?
    - The location data can show the parts of the house where people rarely go, and the interview can determine the reasons for that (*e.g.,* inaccessible or just not used)

- What are key facilitators in people's homes (caregivers, devices, furniture, *etc*.)?
    - The location data can show the routes they take and if an aid was being used. If is not shown being used, then during the interview the participant can be probed about other types of mobility assistance they may use.

3.3.2 The Challenges of Deploying a Location Technology

As is the case with other assistive technology studies, participants are harder to locate than compared to the general population. Therefore, it is often necessary to recruit participants in distant locations. In addition, because of the individual's mobility disability, they have limited ability to deploy any technology themselves. Thus, a deployable system has to be comprised of minimum components that can be installed by anyone, such as by a caregiver or family member. Presumably, researchers would conduct many simultaneous studies to produce a rich and generalizeable result, which argues for a cost-effective and easy-to-deploy solution. PowerLine Positioning is an appropriate location technology to address this need, where the infrastructure requirements are two plug-in modules, and the calibration step consists of a house walkthrough.

3.3.3 Details of the Study

The deployment study involved studying the mobility patterns of four different households (see Table 9 and Table 11). Each household was enrolled in the study for 6 weeks during which 5 interviews were administered on a weekly basis. The first and last interviews were conducted on the days of instrumentation installation and removal. The difference between the two phases is the person that will be installing the PowerLine Positioning system. The installation process during the study was carried out entirely by CATEA employees or caregivers while I played only an observer role. The intention of this was to evaluate the installation and deployment of PowerLine Positioning. I was able to time how long each installation took and interview those conducting the installation to determine ease-of-use and problem spots during the installation. All the installers had a very short training session prior to their attempt at installing the system (see Figures 11-14 for layout of the homes).

For the study, I attached a location tag to each mobility device used and gave a tag to each member of the household (see Figure 17). I built custom mounts that allow easy attachment to round surfaces, such as the frame of a wheelchair or a walker (see Figure 19). Individuals were asked to wear their tag around the neck on a lanyard. The batteries for each tracking tag were replaced or recharged during each weekly interview. However, I found that weekly recharging was unnecessary, because the tags ended up lasting over 1 month.

Table 10 shows the overall procedure for the five-week study for each participant. On the first day, I and the other researchers administered a Home Accessibility Survey, which captures the subject's knowledge, comfort, and satisfaction with their mobility aids and perceived environmental barriers to their mobility device usage during the past week. This survey is a hybrid survey I developed with CATEA researchers that synthesizes various well-known questionnaires from the disability mobility community. Current research measures on environmental barriers in the home are limited to self-report surveys and how barriers are subjectively experienced by the user. I maintained this process so that I could compare the survey data with data gathered from the prompted recall method of using semi-structured interviews based on the mobility pattern data. In the subsequent four interviews, interviewers reviewed the position traces (captured with PowerLine Positioning, see Figure 15 and Figure 16, and Appendix B) with the participant from the previous day and "prompted" them with questions based on the mobility data. The reason for four interviews was to review the data with the participants for four different days of the week, since patterns would be different on different days of the week.

The aim was to compare how much more detail and quality of data researchers can obtain by using the sensed data as part of the interview process, in contrast to relying on self-report alone. For example, one metric of success was the determination of the number of environmental barriers to mobility for that person. Thus, I compared how many more barriers were found with the pattern-based interviews than self-report data to assess its effectiveness.

Table 9: Study overview

Person installing location system	CATEA researchers and assistants
Number of participants	4
Duration per participating household	6 weeks
Number of interviews for each mobility participant	5 (first and last will also involve instrumentation install and removal)

Table 10: Outline of the study procedure for each mobility participant

Day	Procedure
1st day	Administer Home Accessibility Survey and conduct interview (current practice) and perform instrumentation installation. During Phase 2, a survey will also be administered to the installer
End of 1st week	Recharge location tags, interviewer will review location data of prior day with participant and conduct semi-structured interview
One day of 3rd week	Recharge location tags, interviewer will review location data of prior day with participant and conduct semi-structured interview
One day of 5th week	Recharge location tags, interviewer will review location data of prior day with participant and conduct semi-structured interview
Final day of 6th week	Remove instrumentation, interviewer will review location data with participant and conduct semi-structured interview, administer exit survey to mobility participant, I will interview the individual conducting the interviews for this participant

Table 11: Demographic information for each household of the wheelchair mobility participants.

Participant Household	Gender	Age	Profession	Mobility Aids Used	Years Using Chair
1	M	38	IT Specialist	Powered wheelchair	30
2	F	62	Consultant	Powered wheelchair Walker Grabber	26
3	M	51	Public service business owner	Manual wheelchair Manual sports wheelchair	28
	F	48	Sales associate	N/A	N/A
4	F	33	Product manager	Manual wheelchair Walker	12
	M	36	Engineer	N/A	N/A

Table 12: Details of the home for wheelchair mobility participants.

Participant	Year Built	Remodel Year	Floors/ Total Size (Sq Ft)/ (Sq M)	Style	Bedrooms/ Bathrooms/ Total Rms.
1	2001	2001	1/1100/102	2 Bed Apartment	2/2/5
2	1988	1988	1/1600/149	1 Family House	2/2/8
3	1954	1990	1/1800/167	1 Family House	2/2/8
4	1982	1999	1/2400/223	1 Family House	3/2/10

Other quantitative measures of activity gathered through the self-report questionnaire include metrics such as the length of time they spend out of the bed, the frequency that they commute from one end of the home to the other, and the percentage of the time participants spend using each mobility aid and where they use it. With the sensed data, I was able to evaluate the accuracy of self-report responses using these objective measures. Finally, I interviewed the investigators conducting these studies to evaluate the ease-of-use of the pattern traces and its usefulness during the interview process.

For each mobility participant (or household), the interviewer that conducted the HAS-based interview (current best practice) was different from the interviewer conducting the mixed-method interview using the mobility traces. The reason for this was to ensure that the two interview processes do not bias each other. In order to address the issue of the differences between the two interviewers, I attempted to recruit interviewers that have similar experience levels both in conducting interviews and in the disability research community. In addition, I alternated the roles of the interviewer for each participant to counterbalance the interviews and varied when the non prompted-recall interview was administered during the 6-week period.

Inter-rater reliability was used to assess the accuracy of the coding scheme. The goal of inter-rater reliability was to establish consistency in the implementation of the coding scheme. For this study, I had two CATEA researchers code a subject's response based on a pre-determined scale. Then, the coding of participant’s responses was compared between the two researchers to determine if they rated a subject's response the same.

One important consideration was the potential concern participants may have regarding privacy, especially in the home where it is a very personal space. Although the location data did not produce the same level of detail as do video recordings, it was still important to be sensitive to what the participants were willing to reveal. I addressed this concern in two ways. The first was by giving the participants the ability to stop collecting location data at any moment by pressing the button on their location tag. Pressing the button again would restart data collection. The second was by creating a trusting relationship with the interviewer during the data review and interview process. This was accomplished by initially sharing with them their mobility trace data. Trust was also established by making participants a partner in the research process and having them drive the interview by asking them to walk through their day with the interviewer. The interviewer in turn asked more specific questions based on what the participant chooses to reveal and what they saw from the mobility trace. In addition, the interviewers were instructed to be sensitive to questions and/or issues participants might find invasive and uncomfortable.

On the final day of the deployment, I also administered an exit survey to the participants that collected data about the comfort of the PowerLine Positioning tag, their impression of the system, its aesthetic appeal, and any burden it caused the participants.

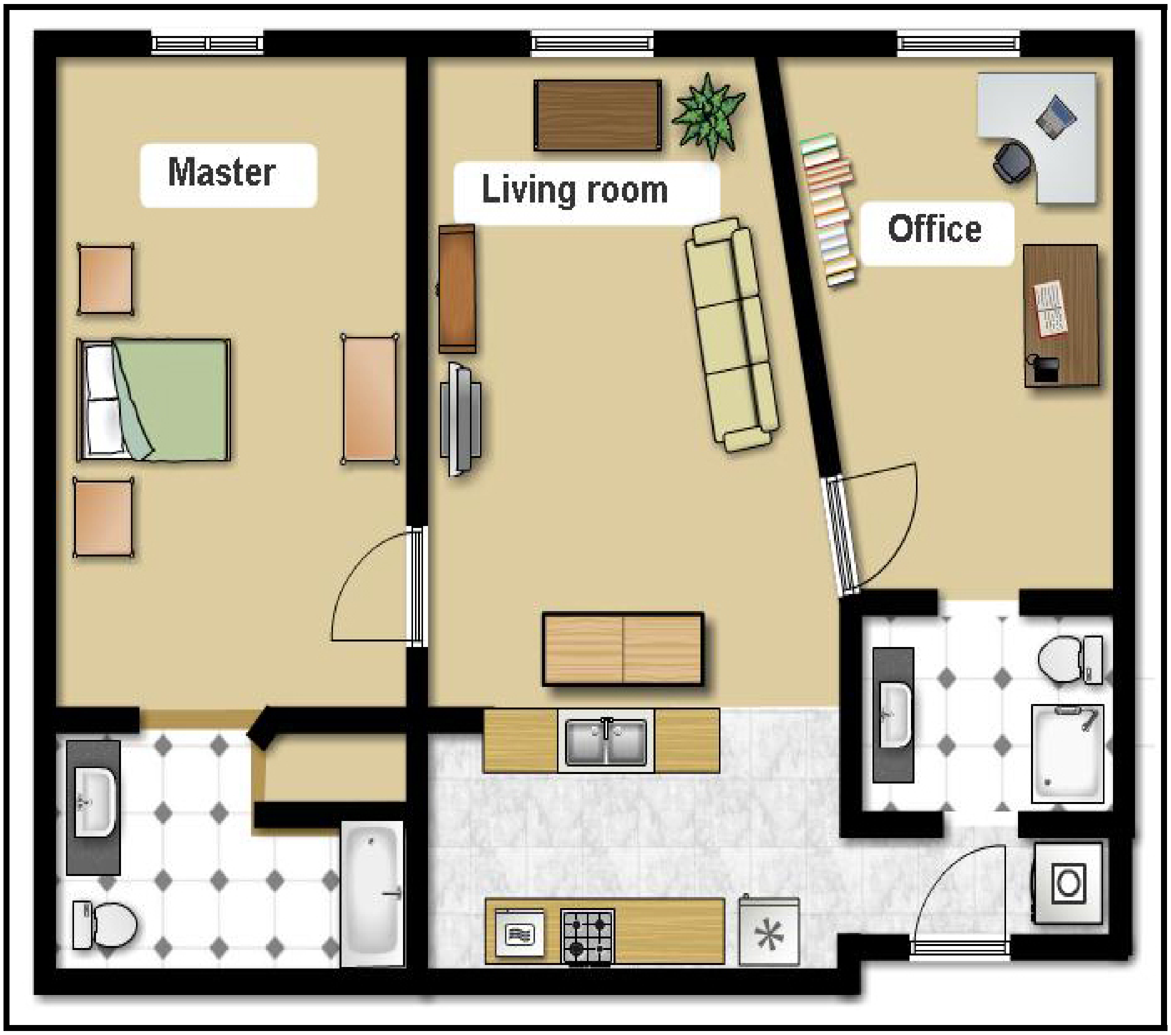


Figure 11: Layout of Participant 1's home.

Figure 12: Layout of Participant 2's home.

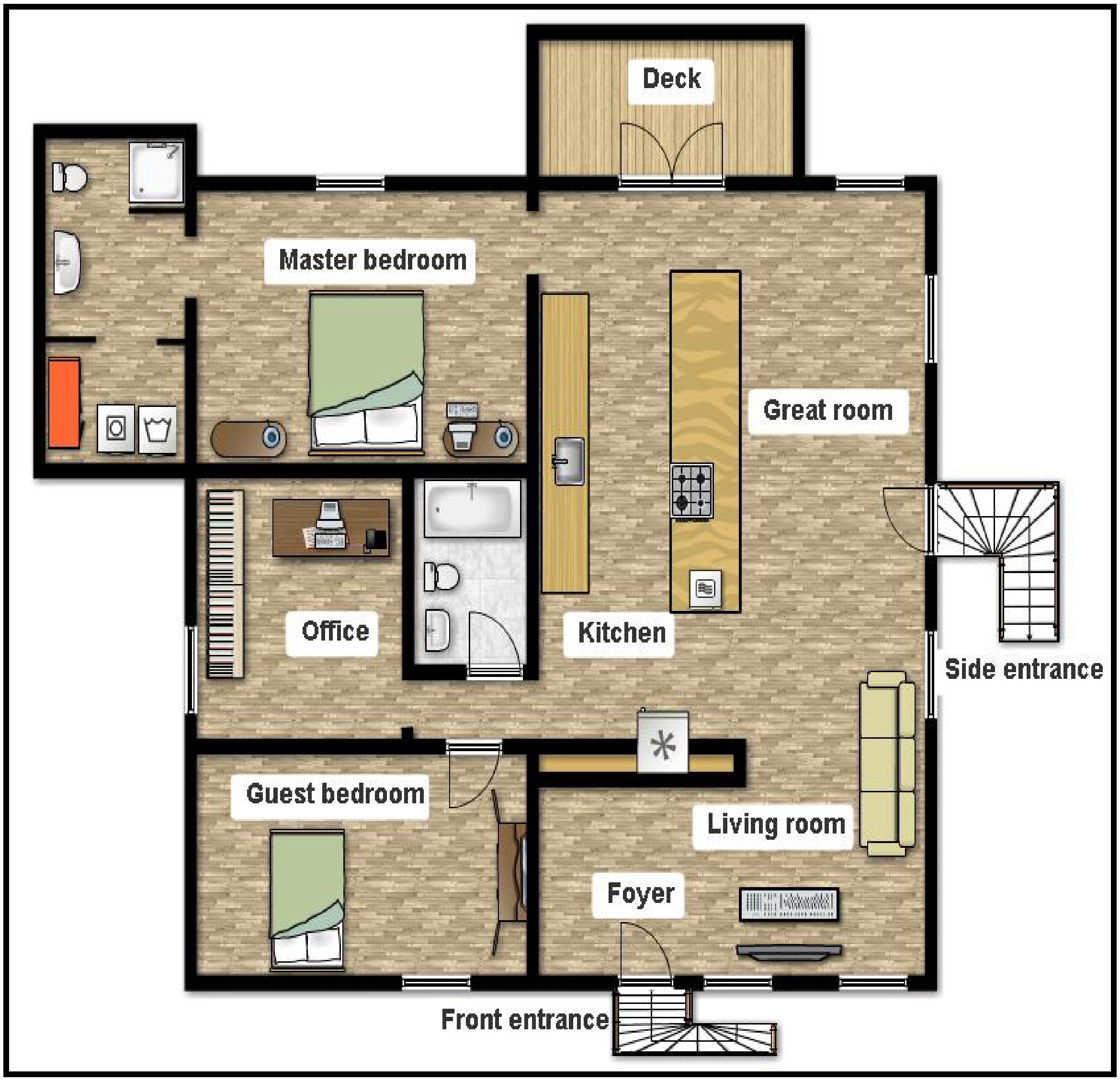


Figure 13: Layout of Participant 3's home.

Figure 14: Layout of Participant 4's home.

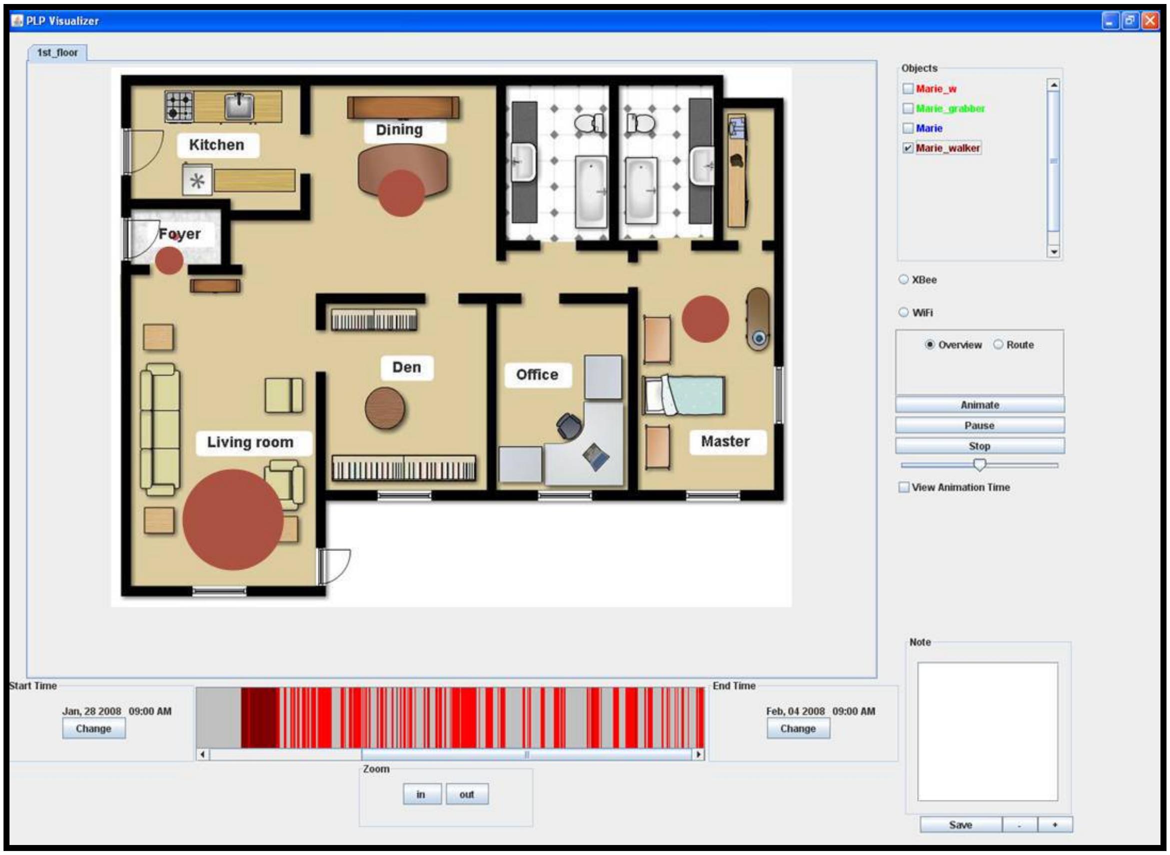


Figure 15: Visualization of PowerLine Positioning data that was used during the interviews. This particular screenshot shows the overview of how long tracked entities were at particular locations (based on the size of the dot). The tool allows a time range to be selected and the scrollable timeline can also be zoomed in and out. The colored vertical bars represent movement of the corresponding entity. Bars can be placed by the user to indicate the temporal range shown on the map.

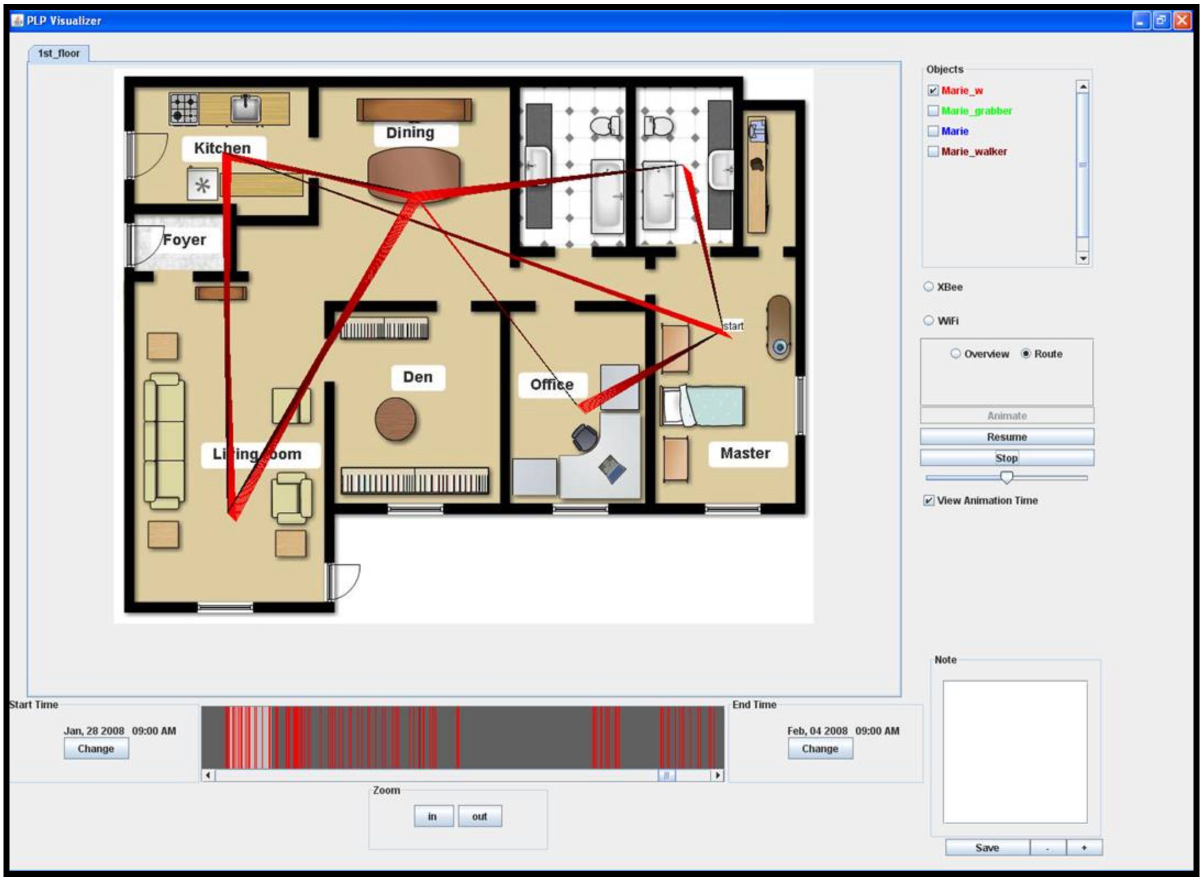


Figure 16: This screenshot shows the mobility trace or routes of the tracked objects and people. In this view, the black bounding bars on the timeline are used to indicate how long of a trail to show on the map. The routes are drawn as a line segment on the map to show the origin and destination. The interface also supports replaying the exact route taken in the house.

Figure 17: Upper Left: Deployable PowerLine Positioning tag. Upper Right: Wearable encasement used to house the tag and the battery pack. Bottom: Encasement used for larger devices, such as wheelchair and walkers. The larger case housed a higher capacity battery.

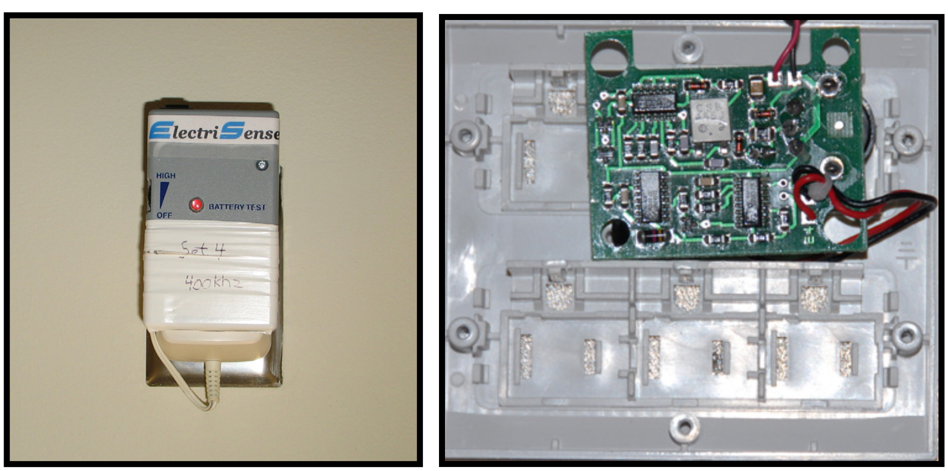


Figure 18: Left: The signal generator plug-in modules. Right: Inside back cover of the outlet expander housing the signal generating circuitry.

Figure 19: Sample placement of a PLP tag on a participant's wheelchair

3.3.4 PowerLine Positioning Deployment Results

The performance and ease-of-deployment of the PowerLine Positioning system were assessed by comparing it to Ekahau, which is a commercially available WiFi-based indoor location system. Both PLP and Ekahau were installed for the wheelchair mobility study. For each of the four deployments, CATEA researchers installed the two systems, and I evaluated the installation and maintenance for each. Both PLP and Ekahau involve a similar installation and calibration process, with PLP requiring fewer hardware components. I trained two researchers, who did not have any previous experience in installing either system, before the installation of these systems. The training involved a 30-minute tutorial and an installation example in a laboratory. Both the PLP (see Appendix B) and Ekahau installation manuals were provided to the installers to read beforehand if they chose to do so. The installers also observed and helped in the installation process in the pilot homes prior to the start of the study. For the actual study, each of the two installers installed both systems in two homes.

Overall, both systems were successfully deployed in all four homes. Figure 20 depicts the installation time of each system in each home. The time includes the planning, physical installation, calibration, and testing of the system. When the tracking system reported close to 100% accuracy from 20 random locations throughout the home, the installation process was concluded. From the results, it is clear that PLP took less time to install than Ekahau, especially in Home 3. PLP took an average about 30 minutes to install, while Ekahau took over 1 hour to install. Interestingly, the shortest time to install Ekahau was still longer than the longest PLP install time. In addition, Homes 1 and 2 were installed by one installer and Homes 3 and 4 by the second. The second installer did take longer for the installation, but there was a significant difference between the two tacking systems.

The major factor that contributed to the difference between PLP and Ekahau was not only the number of components required for the installation, but also the positioning and repositioning of the hardware component. In the case of Ekahau, 15-20 WiFi base stations were needed to provide sub-room-level localization. The installation process not only involved installing those base stations, but also potentially required relocation of those base stations to increase coverage or spatial differentiability in a particular area. This trial and error process greatly contributed to the longer deployment times. In Home 3, Ekahau had to be calibrated three times during the installation process, which contributed to its lengthy install time. PLP, on the other hand, required very little hardware that needed to be installed. In addition, the spatial differentiability results from the power lines itself, so significant repositioning is not required.

During the study, I conducted performance tests when meeting with the participants for their interviews to determine whether recalibration was necessary. A recalibration was determined to be necessary if more than 10% of the tests failed to produce a correct position reading. Figure 21 shows the number of times each system had to be partially recalibrated. Home 1 required part of the living room and master bedroom to be resurveyed, due to a performance degradation noticed during the second week. The other 3 homes required no additional surveys. However, Ekahau, required many resurveys, with Home 1 requiring a recalibrate during each visit. The reason for the degradation in performance was because the signal strength of the WiFi access points weakened overtime, even after one week. In addition, the fingerprints changed over a short period of time. Although room-level localization accuracy of Ekahau was reasonable, sub-room-level performance varied greatly between each week. Finally, Figure 22 shows the total times spent installing and maintaining each system. A significant amount of time was used for the calibration or recalibration of the systems.

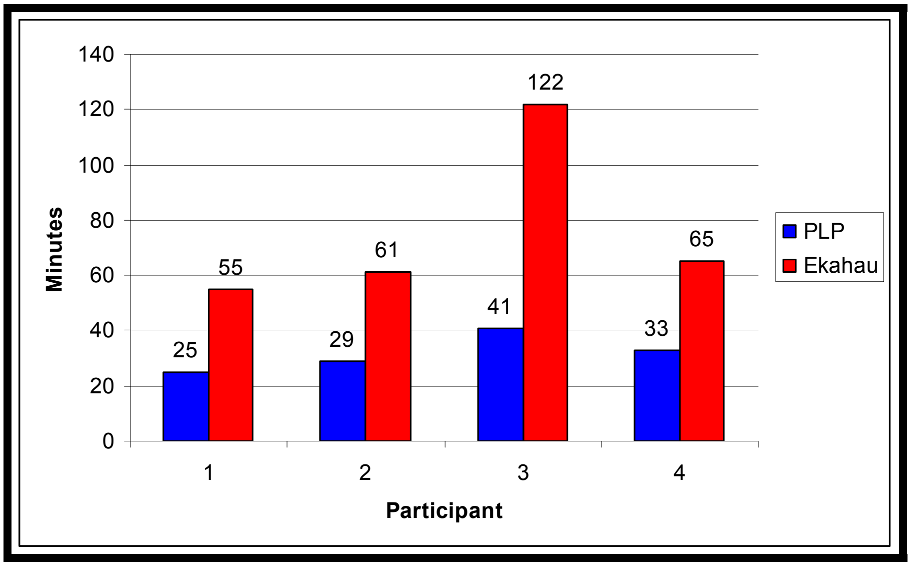


Figure 20: Tracking system installation time (in minutes) for each of the four households.

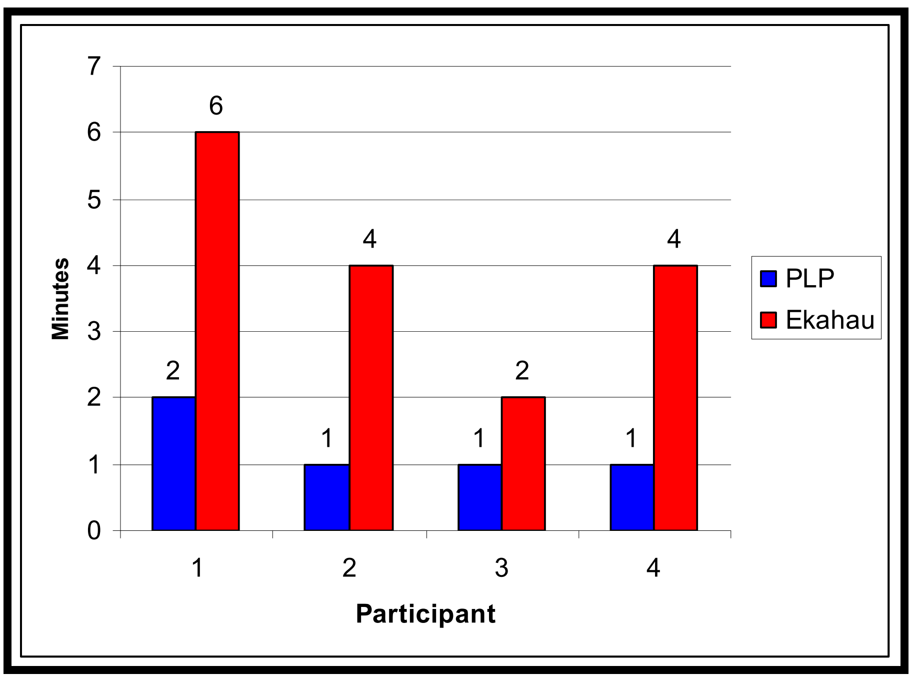


Figure 21: Number of times the tracking systems required a recalibration during the entire study for each of the participants.

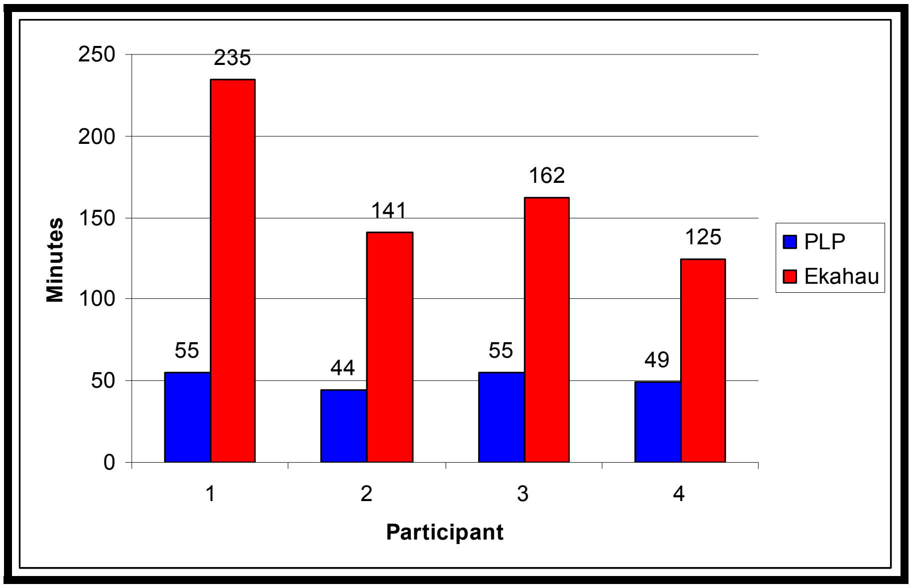


Figure 22: Total maintenance time (in minutes) for the entire study. This includes any recalibrations or technology updates/upgrades.

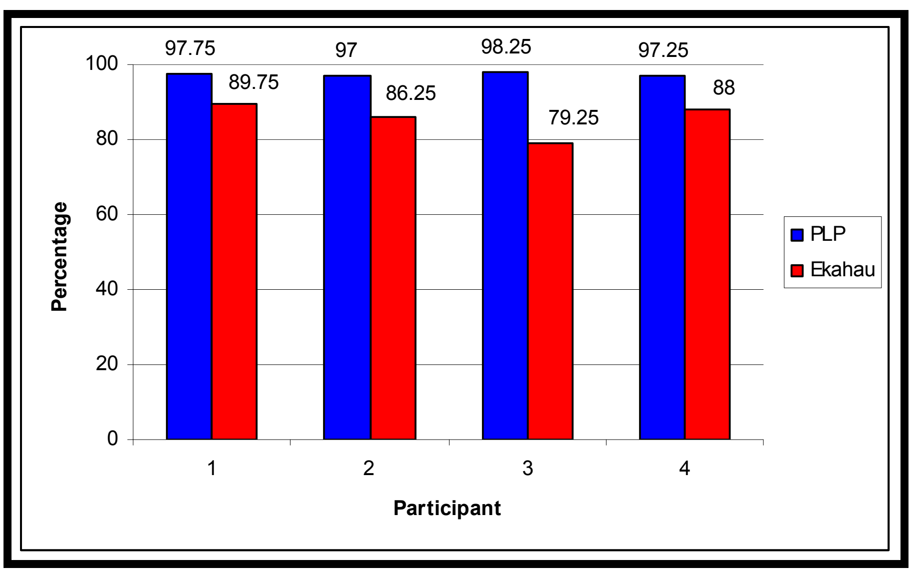


Figure 23: Participants manually labeled ground truth data throughout the day by simply pressing a button placed at a fixed position in the house. This chart shows the percentage of time the location tracking system correctly showed the person's location at the time the button was pressed.

3.3.5 Wheelchair Mobility Study Results

The aim of this study was to evaluate what role PowerLine Positioning can play in collecting objective data about wheelchair users in their home. In addition, I wanted to explore the value of using PLP in the proposed mixed-method prompted-recall approach. In this study, I wanted to explore how I could support CATEA researchers in studying the mobility patterns of wheelchair users. The goal was to apply this prompted-recall approach to the wheelchair mobility study and compare it to the current best practice of self-report surveys and interviews.

The study involved four different households (see Table 9). Each household was enrolled in the study for 6 weeks during which for each household at least two PLP-based prompted-recall interviews and two prior practice surveys and interviews. The prompted-recall interview consisted of a 1-hour meeting with each participant and a walkthrough of his or her previous two days using the PLP tracking data (see Appendix A for interview guides). The participants were allowed to dictate what was shown on the tracking interface to talk about any detail they chose, but the interviewers were instructed to follow the interview guide as much as possible. The tracking data was used to help prompt the participants about interesting situations that might have occurred with their mobility aid. In addition, the data was also used to encourage the participants to reflect on their usage of various mobility aids. The non-prompted interview was conducted using an adapted version of CATEA's current practice surveys (see Appendix A). These interviews also lasted about 1 hour, and the interviewers were asked to follow the interview guide. The interview was very similar to the prompted-recall interviews except the tracking data was not available. The interviewers asked each participant to reflect on their previous two days during their interview, although they were not limited to that.

Each interview was audio recorded, and the PLP tracking software logged when various features of the software were used. The interviewers also took notes during the interview. After the completion of the study, the interviews were transcribed for further analysis. The PLP tracking data was also analyzed to extract quantitative measures, such as time spent in each room, percentage of each used throughout the date, *etc.*, to compare against the participants' recall of that information.

The results and analysis are divided into three sections. The first reports the findings relating to the quality of the interview process itself with and without the use of PLP. The second is the use of the PLP tracking interface during the interview process. The third is the objective quantitative data uncovered with PLP and its comparison to the self-reported data from the study.

3.3.5.1 Evaluating the Prompted-Recall Interview Process

The interview notes and transcripts were used to extract relevant statements and discussion points generated during the interviews, which in turn were used to produce themes that emerged from all the interviews relating to mobility problems. Two researchers independently categorized the statements in the transcripts and notes to determine the themes. The two coders produced a total of 19 themes, eight of which were common across the two coders. Thus, 11 unique themes were included after discussion and resolving overlaps between the different themes. A third independent coder re-categorized the statements using these 11 themes and an inter-rater reliability was calculated using the categorizations from the three coders (see Table 13). Inter-rater reliability for each theme was determined using two different measures. First, observed agreement was determined, which is the measure of simple agreement between the two coders for each theme. Observed agreement is measured by agreements divided by total number of statements coded. Second, Cohen's Kappa was determined, which measures how much better than chance the agreement between the coders is.

The following themes emerged after the data analysis:

1. *Mechanical problems*: physical problems with the mobility aid itself, such as a broken wheel, faulty brake, *etc.*
2. *Mobility aid form factor or design problems*: the aid does not serve its purpose or intended function
3. *Doorway, hallway, or threshold barriers*: problem in locomotion in the home because of environmental barriers
4. *Reach problems*: items of interest being out of reach
5. *Level access problems*: this includes accessing items that hard to maneuver to, which can result from not being able to rotate the wheelchair, cluttered room, *etc.*
6. *Exercising*: tasks relating to regaining mobility strength, such as home physical therapy
7. *Safety concerns*: afraid of falling or not being confident enough to go to a particular region of the house or perform a particular task
8. *Person assistance*: task requires assistance from an able-bodied individual
9. *Floor conditions*: the characteristics of the floor contribute to mobility concerns, such as using a walker on carpet or slippery floors

10 *Self conscience*: reluctant to show they used a mobility aid

11 *Medical procedures*: recent medical procedures or changes in health affecting overall mobility

Both interview methods (prompted-recall and non-prompted-recall) produced responses in nine of the 11 themes (see Table 15). However, two themes (Theme 6 and 10) only emerged from the prompted-recall data, In addition, a higher percentage of discussion points relating to Themes 5, 7, and 8 were produced from the prompted-recall data. Thus, there were some clear advantages to having the tracking data available during the interview process. For example, topics relating to mobility and exercising did not come up in any of the self-report data. In the case of exercising, participants often talked about using a particular mobility aid for the purposes of strengthening their legs or muscles. However, it was not until participants actually saw their activity data did they recall this detail. Similarly, reflecting on their tracking data also resulted in participants discussing situations about other individuals having to help them with a particular task. Many participants also discussed situations where they did not take a particular route in their home or use a particular aid in certain parts of the home because they were afraid of falling (Theme 7).

Table 13: Inter-rater reliability for each theme was determined using two different measures: (1) Observed agreement, which was the measure of simple agreement between the two coders for each theme and was measured by agreements divided by total number of statements coded; (2) Cohen's Kappa measures how much better than chance was the agreement between the two coders. Measures are between 0 and 1, with 1 indicating perfect agreement between coders.

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Observed Agreement	.96	1	.96	.98	.95	95	1	.96	1	1	.95
Cohen's Kappa (k)	.92	.96	.83	.95	.79	.80	.96	.79	.94	,96	,80

Table 14: Inter-rater reliability for the value assignments: (1) Shows observed agreement. (2) The Cohen's Kappa measure.

Coded statements	**Observed Agreement**	**Cohen's Kappa (k)**
113	.96	.88

Table 15: Percentage of discussion points resulting from prompted-recall and non-promoted-recall interviews for each theme.

Theme	**Percentage resulting from prompted-recall (%)**	**Percentage resulting from interview w/o PLP (%)**
1	36	**64**
2	44	**56**
3	**51**	49
4	**53**	47
5	**86**	14
6	**100**	0
7	**75**	25
8	**80**	20
9	36	**64**
10	**100**	0
11	39	**61**

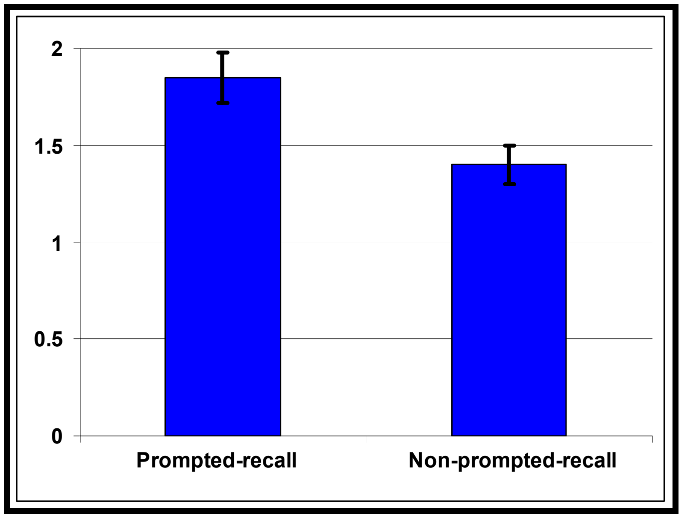


Figure 24: Comparison of the average rating (with errors bars) for all coded statements and discussion points of the two interview methods. Coders rated each discussion point with a value of 1 or 2.

Finally, an interesting result from the prompted-recall data was that participants not only talked about physical barriers in their environment, but also social pressures (Theme 10). For example, there was one instance where the data showed that a participant started to use a different aid that was not normally used. When she saw this, she stated that she did not want to her grandchildren to see her in a wheelchair, so she made a conscience effort to use the walker during their visit. Another participant reported using a manual wheelchair when his friend would come over, who also used a manual wheelchair.

In addition to counting the number of themes that emerged with each approach, a second coding scheme was introduced to rate the quality of the coded discussion points. Two coders rated each of the 113 statements or discussion points around that statement with a rating of 1 or 2. A value of 1 referred to a statement that was mentioned, but the participant did not engage in supporting details or examples during that discussion, while a value of 2 was given to a discussion point that involved the participant giving specific details. I also calculated a percentage agreement and Cohen's Kappa for the rating scheme (see Table 14). The aim of this coding scheme was to determine the number of rich discussion points that resulted from using the prompted-recall method compared to the standard interview. Figure 24 shows the average rating from for two interviews. The higher rating of the prompted-recall interviews appears to be a result of the participants having something to explain or narrate when using the tracking data. In the self-report data, it was often the case that participants rarely remembered details around their actions during the prior days. One participant referred to the tracking data as "the next best thing to a video camera without a camera," alluding to the usefulness of the context it offered during the interviews.

3.4 Summary of Contributions

- PowerLine Positioning is a new technology that supports the localization of objects and people in the home with minimal additional infrastructure
- Technical evaluation of the system to determine its performance and a comparison to other similar approaches
- Deployment of PowerLine Positioning in an actual tracking-based research study
- Evaluation of the ease-of-use and deployment of PowerLine Positioning and its ability to scale to many simultaneous deployments
- Evaluation of the improvement of the quality of qualitative and quantitative data of prompted-recall over self-report

CHAPTER 4

THE PROXIMITY BETWEEN PEOPLE AND OBJECTS

In Chapter 3, I discussed a technology capable of providing sub-room-level location information in a home and the use for that kind of technology. In this chapter, I discuss a technique to track the relative proximity between people and objects in any space, not just in the home, the kind of study this enables, and a look at an in-depth study that uses this method.

4.1 Studying People and Objects Outside the Home

Interesting behavior between people and objects does not just occur in the home, but can extend outside the home as well. However, the location of people and their relationship to objects is much harder to track automatically in an unconstrained environment. Even location technologies, such as global positioning system (GPS), do not offer the resolution to discern actions between a close group of individuals and objects. In addition, GPS requires line-of-sight operation, thus limiting where the tracked items can be placed. Alternative investigation methods such as ethnography, surveys, interviews, and experience sampling methods do not always produce data for the entire day without burdening the participant. Often, it is desirable to collect data in a way so as not to draw the user's attention to it, which may affect their behavior.

One particular class of problems where technology can play a key role is in studying the physical proximity between people and objects. This is useful when studying how often users are near certain objects or individuals throughout the day in order to study adoption or gather contextual information of the surroundings.

4.2 BlueTrack Overview

BlueTrack is a general-purpose system capable of determining the proximity between tagged objects and people. BlueTrack uses Bluetooth technology for its implementation and has a number of advantages. The popularity of Bluetooth devices has greatly driven down the cost of its components, which makes it an affordable solution compared to proprietary radio systems. In addition, devices that already incorporate Bluetooth technology, such as mobile phones, laptops, Personal Digital Assistants (PDAs), and automobiles, interoperate with the system, thus minimizing the number of objects that have to be instrumented. BlueTrack software can run on a variety of platforms, including personal computers and mobile phones. Devices with the BlueTrack software (mobile phones, laptops, other BlueTrack tags, *etc.*) can determine three levels of proximity to BlueTrack tags (see Figure 28), which equate to roughly within arm's reach (within 1-2 meters of the tag), within the same room (within 3-6 meters of the tag), and unavailable beyond 6 meters from the tag. Unlike previous Bluetooth ranging attempts, devices running BlueTrack software do no have to pair with BlueTrack tags. The ranging is accomplished using the Service Discovery Profile (SDP) layer, which also allows for substantially improved battery life.

4.2.1 BlueTrack Implementation Summary

The BlueTrack tags are ABS plastic encased beacons that consist of a low-power CSR BlueCore-02 Class 2 Bluetooth RF module with an integrated antenna and a 3.7 V 345 mAh lithium ion battery. The tag can signal every minute for approximately five days with a single, two-hour charge. A buzzer and LED on the tag indicate when the battery is low. The tag uses a Class 2 Bluetooth module with a 10 meter range, which is sufficient for registering the levels of proximity of interest and uses much less power than the longer range Class 1 modules. The Bluetooth stack implements the Serial Port Profile (SPP) running over L2CAP and RFCOMM for firmware programming. The Bluetooth radio in the user's beacon was reduced to -22 dB to extend battery life and limit the maximum range at which the mobile phone can detect the tag to around 5 to 6 meters. The design of the radio output and subsequent distance analysis assumed a tag placed around the neck of an average adult.

Rather than use a Received Signal Strength Indicator (RSSI), which is implemented inconsistently across mobile phones if at all, I implemented my own simpler signal strength indicator for proximity detection. In this solution, the round trip time of the Service Discovery Protocol (SDP) packets is used to estimate the distance between the tag and the mobile phone. As the distance increases between the mobile phone and the tag, the link quality should degrade. The lower link quality then increases the bit error rate and thus the number of packet retransmissions. The retransmits in turn increase the service discovery time. Despite the simplicity of this approach, it was more than sufficient for the level of granularity desired for this study.

By reducing the radio output of the tag, I can specify a rough range at which the bit error rates increase by a set amount. After experimentation in lab settings with humans of average size, I determined the appropriate range values. A phone within arm's reach typically shows a service discovery time of about 2000-4000 ms (1-2 meters), room-level distance (3-6 meters) of about 4000-7000, and no returned service discovery information is interpreted as the phone being out of range or further than room level (6 meters). In practice, physical room level distance can result in fluctuating values between 4000 ms and no discovery. This fluctuation is likely due to a bit error rate that is so high the Bluetooth module times out and does not report a successful service discovery. One serious issue with this phenomenon is the difficulty that results in determining whether the phone is transitioning from “room level” and truly out of range or whether the phone is consistently at room level with the erroneous fluctuation described. Thus, if I observed high rates of fluctuation (*e.g.,* alternating with every reading) over extended periods (more than five minutes), I classified the reading as room level.

4.3 Evaluation of BlueTrack

I conducted various technical evaluations of the BlueTrack system to determine its operations parameters and its performance. In addition, BlueTrack was deployed in one of my own research studies that involved the in-depth empirical investigation of the proximity of users to their mobile phone.

The overall aim of the deployment study was to answer the following thesis claims:

- Can BlueTrack provide objective empirical data for proximity-based studies?
- Does using automatically sensed data using BlueTrack facilitate a richer interview process that produces better quality data than traditional methods of self-report?

4.4 BlueTrack Technical Evaluation

The BlueTrack technical evaluation consisted of three experiments. The first was a laboratory experiment that consisted of individuals wearing the BlueTrack tag around their neck on a lanyard, and round trip time readings were taken (with a mobile phone) at varying positions around the individuals. I ensured that all measurements were taken at approximately the same horizontal plane. This experiment served to determine the appropriate radio detuning values and the determination of the round trip times for the three proximity levels. Figure 25 shows a plot of the maximum range of the tags at varying positions around an individual wearing the tag. As seen in the plot, the maximum range of the tag is about 1.5 fewer meters when it is behind the person wearing the tag. This is mainly due to the reflection and absorption of the 2.4 GHz signal. Thus, my aim was not to provide precise fine grain ranging, but offer more accurate ranging at a lower resolution.

The purpose of the second experiment was to evaluate the accuracy of the three levels of prediction. The second evaluation was similar to the first one in that it consisted of an individual wearing the BlueTrack tag around his neck on a lanyard. Proximity readings were taken at varying positions around the individuals. The ground truth distance was compared to the predicted distance (arm's length, room level, or not available) at each point. In the experiment, a total of 75 positions (25 in arm's length range, 25 in room-level range, and 25 out-of-range) were selected around the individual, and at each position, 10 proximity readings were taken. Thus, 750 readings were taken. This whole process was carried out for two different individuals. Figure 26 shows the results of the overall, arm's length-level, room-level, and out-of-range accuracies. Upon further investigation, many of the classification errors came from the room-level value being classified as out-of-range. This fluctuation is especially apparent near the 4-6 meter point where it is near its maximum range. As a result, during the data analysis and interview phase, I took care to determine whether this fluctuation was due to actual room-level and out-of-range transitions or if it was an incorrectly classified room-level value.

The third evaluation was to test BlueTrack in a more natural setting. I deployed the application with two individuals and asked them to keep a diary that logged each time they transitioned between one of the three levels. The diary entry included the time and the one of the three distance measures. Each participant collected approximately 50 samples in a 48-hour period. Because of the tedious nature of this investigation, I was limited to the number of test samples, but still obtained enough data to provide some insights in its performance. Figure 27 shows the results of the different levels of proximity. The results are similar to the laboratory study despite the limited number of samples. Also similar to the laboratory experiments was that the room-level proximity classification has the lowest performance and was mainly due to incidents incorrectly being classified as out-of-range.

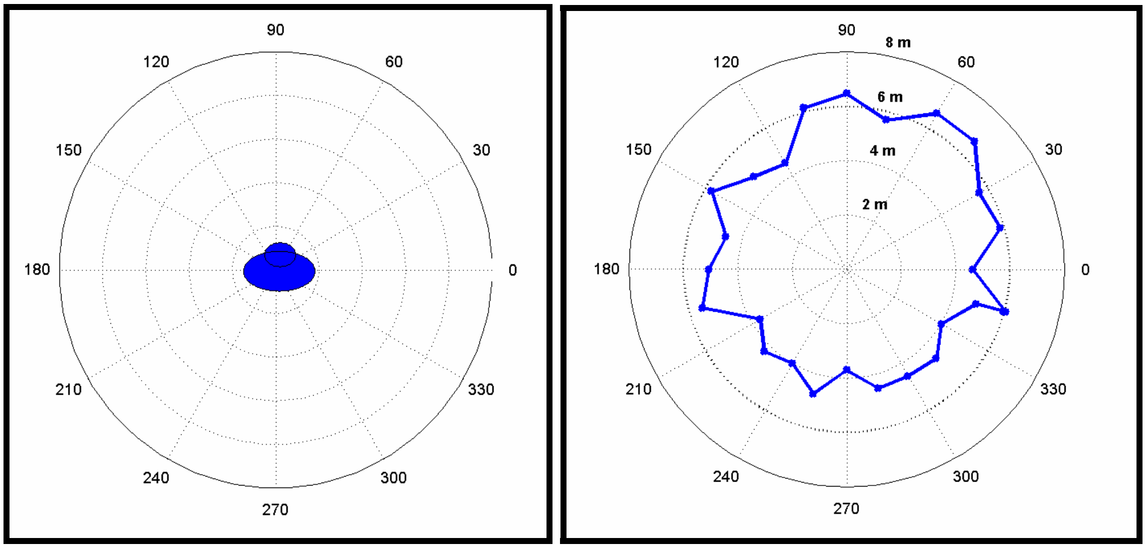


Figure 25: Left: This figure shows how the laboratory experiments where conducted. An individual was facing forward (towards 90 degrees) with the BlueTrack tag around the neck. Right: After reducing the power of the radio, these were the maximum read ranges at various places around the individual. The approximate range is about 5-6 meters. Of note is the 1.5 meter decrease when readings were taken from directly behind the individual.

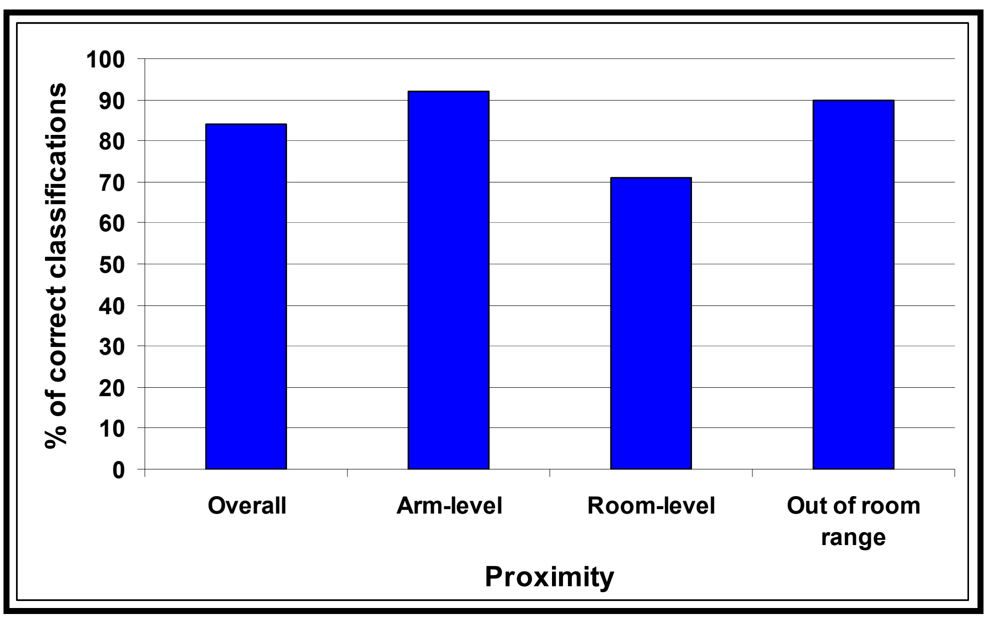


Figure 26: The percentage of correct proximity classifications in the laboratory setting. A majority of the incorrectly classified room-level values were classified as out of range.

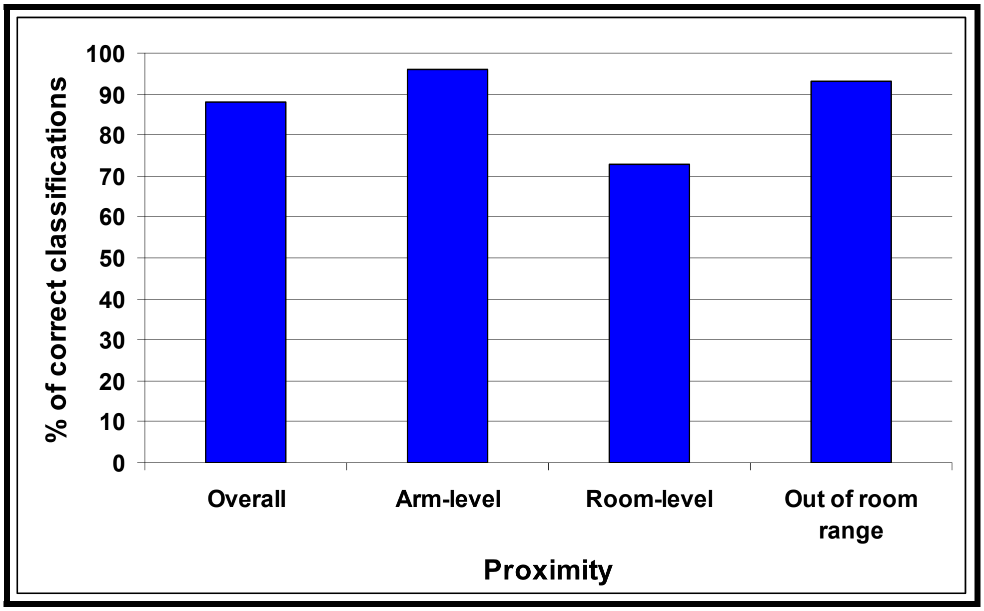


Figure 27: The percentage of correct proximity classifications from the diary study.

4.5 Deployment Study – The Proximity of a Person to Their Mobile Phone

Mobile computing systems have been one of the fastest evolving and growing technologies of the last decade. The increasing power and ubiquity of these mobile technologies make it possible to realize many of the early visions of ubiquitous computing. Many argue that the mobile phone, with its expanded capabilities, can be the platform of choice for applications that once required customized mobile hardware [114]. Examples of research focused on these expanded uses include memory aids [43], augmented cognition [47, 118], location-based services [67, 93], medical data collection [129], authentication mechanisms [20, 99], and personal information stores [131].

The topic of location has been a common discussion point in ubiquitous computing with researchers making the mobile phone the platform of choice for location-aware computing. The PlaceLab effort at Intel Research and other location systems (see Chapter 2) have demonstrated that ubiquitous location-awareness can be delivered on commodity hardware, most interestingly mobile phones [67, 93]. This advance creates many opportunities for developing knowledge on the mobile phone of where a person has been and what they have been doing. However, this approach assumes that the mobile phone is an accurate proxy for the location of its owner. Intuitively and anecdotally, people do in fact carry their mobile phones with them much of the time, but these same phones are neither physically on their bodies nor within arm's reach at all times.

Many researchers and application designers make the implicit assumption that people are likely to have their mobile phones with them and available most of the time. However, little empirical evidence on the actual proximity relationship between a mobile phone and its owner exists. Thus, I wanted to conduct an in-depth empirical study to uncover the habits of a set of mobile phone users. This work not only tests the hypothesis that a user's phone is available to her most of the time but also provides an exploration of the situations in which the proximity assumption is broken and attempts to select the factors that best predict the proximity relationship. Through this evidence, it is possible to create concrete design advice for mobile phone applications that require knowledge about the proximity of the user to her phone.

This work provides the following four contributions. First, I present the design and creation of a proximity-sensing technique and the design of an empirical proximity study that can be replicated by others. Second, I present empirical evidence directly testing the strength of the assumption that the mobile phone is a good proxy for its owner's location. Third, I present a classification of situations that break the proximity assumption, which can be interpreted as design advice for mobile phone applications.

Fourth, I present a decision tree method for predicting proximity to mobile phones based on readily accessible features on the phone itself.

4.5.1 Overview of Proximity Study

The mixed-method prompted recall approach was used, in which I use both interviews and automatic logging to develop a full picture of user practices. I collected data about the phone and about its owner to help understand and potentially predict the proximity relationship between owner and phone. These data, initially collected automatically, were verified using self-report.

A primary goal of this study included gathering information about users and their mobile phones all day every day for some extended period, which introduced minimal burden and did not rely on self-report [22]. Due to the increased capabilities of mobile phones, it was possible to gather much of the data using software developed for that platform. Recording the user's physical relationship to the phone, however, required a reliable proxy for the user, thus I used the tags from the BlueTrack system (shown in Figure 28). I was thus able to measure the phone's distance from the tag and assume this roughly equated to the phone's distance from the individual.

The BlueTrack application on the user's mobile phone stores a distance measure every 60 seconds (within arm's reach, in the same room, or unavailable). A separate application on the user's phone recorded contextual information, including signal strength, battery level, charge status, current running application, cell tower ID, area ID, ring volume, ring type, and vibration status. A third application inherent to most mobile phones logged incoming, outgoing, and missed calls, the number of SMS messages sent and received, and data usage.

Sixteen individuals participated for at least three weeks each. All of the subjects lived in the greater metropolitan area of Atlanta, Georgia, USA and were recruited via word of mouth and Internet classified advertisements. Participants were compensated with $200 for completing the entire three-week study and returning the equipment. Participants ranged in age from 21 to 66 and included 9 males and 7 females. Self-reported phone plans ranged from a 5000 minutes per month contract to a prepaid, "emergencies only" service plan. Participants also had a wide variety of professions and income levels (see Table 16). Each participant completed a background interview to provide basic demographic information and data on perceptions of individual phone usage patterns. These questions included those about current phone-charging patterns, applications used on the phone, service plan information, and the perceived phone proximity throughout the day. In addition, participants where also asked to self-report on their proximity habits to their mobile phone in as much as detail as possible.

After the initial interview, the participant's phone was replaced with one of several form factors, all capable of running the logging software, accomplished by a simple swap of SIM cards. I copied all contact list information over to the new phone by using the SIM card's memory or, in rare situations, manually entering the information. I provided phones of a similar form factor and with similar software and menu structures to the phones already in use by the participants. Thus, I believe that the phones had minimal impact on the practices of the participants. Participants received a tag and instructions about charging the phone and the tag. They were instructed to use their phones as normal and to wear the tag at all times. Notable exceptions included while showering or swimming. Most subjects wore the tag while sleeping, but others preferred to place it next them while sleeping. If they removed the tag, they were asked to note the time and duration and keep the tag as near as possible.

During the three weeks of participation, the individuals met with me or other researchers once per week during which I downloaded the logging data from the phone and interviewed them about their usage patterns for the week. At the beginning of each interview, the participant completed a detailed diary of the previous 24-hour period, as suggested by the Day Reconstruction Method [58], breaking the day into episodes described by activities, locations, and the phone's location during these times (see Appendix C). During these interviews, participants reported reasons they did or did not have their phones for various episodes reported on the diary. Together with the participant, I then compared this diary to the data recorded by the logging application (showing them visualizations of phone proximity) and asked clarifying questions for any inconsistencies (see Figure 29 and Figure 30). The self-report and visualization could disagree for three reasons:

(1) The participant may have an error in recollection.

(2) The logging application and/or the hardware itself could produce an error.

(3) The tag was not an appropriate proxy (*e.g.,* the user was not wearing it).

The review process also allowed for the interviewer to ask more specific questions based on interesting patterns seen in the proximity visualization.

The interview closed with general questions about the remaining days from the preceding week, such as whether it was a normal workday or a day off, but did not include any specific details about the days that were further in the past. On the third and final interview for each participant, equipment was returned and replaced with the participant's original phone.

Figure 28: Tag used in the BlueTrack System

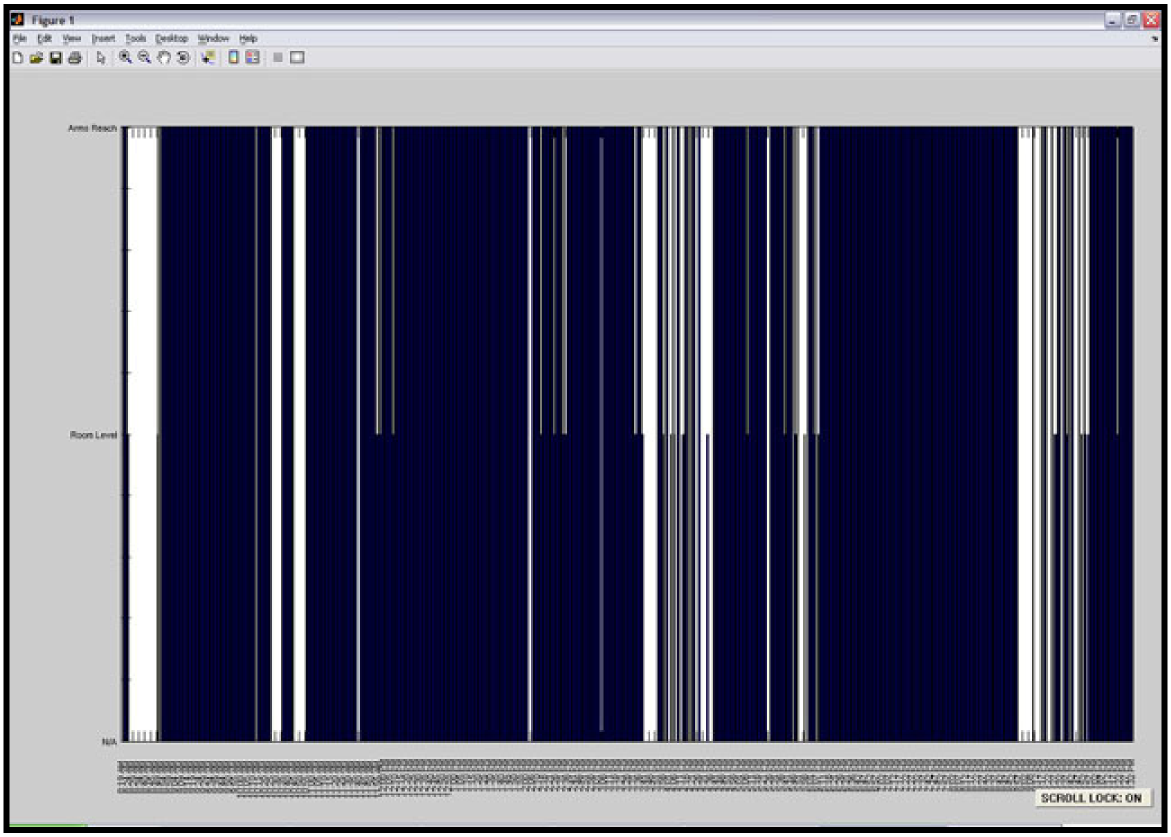


Figure 29: Visualization showing about 12 hours of proximity measures. The full solid lines indicate the tag is within arms reach, the white indicates that it is not available and halfway between or oscillating indicates the tag is at room level.

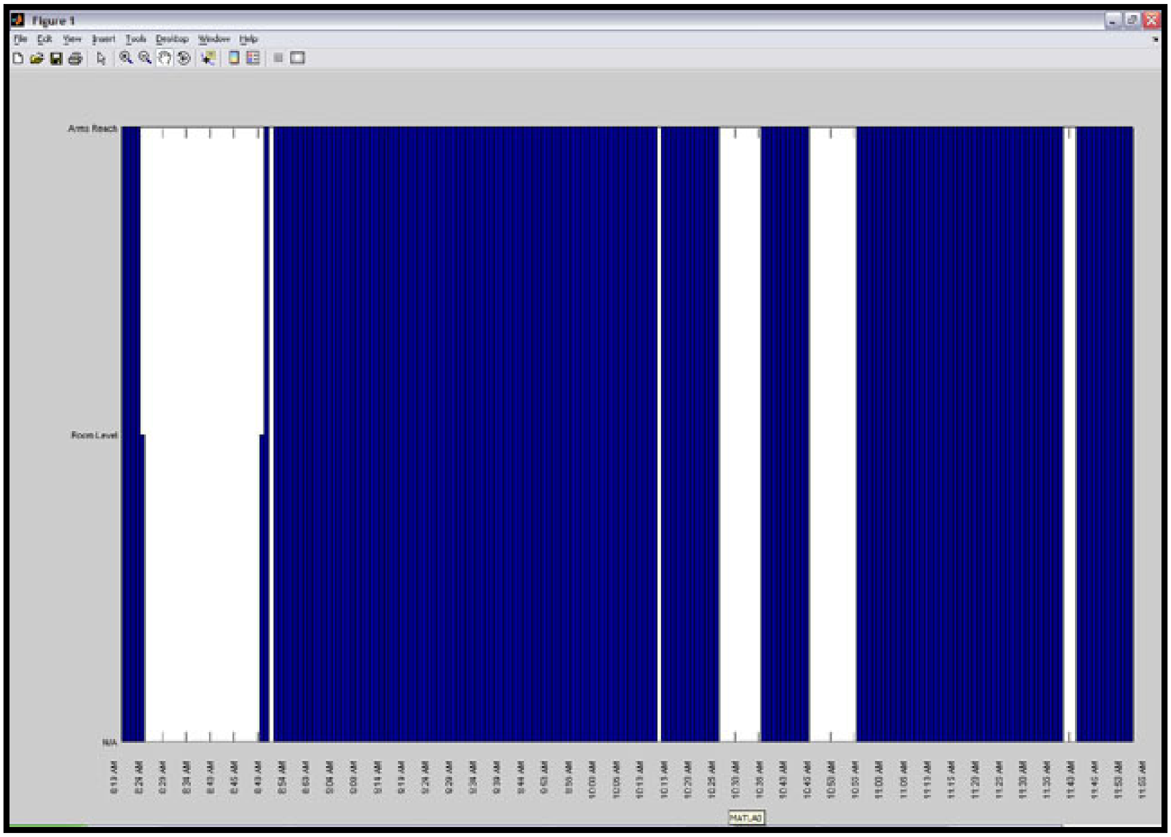


Figure 30: A zoomed in view of the visualization showing about 2 hours of proximity data.

Table 16: Demographic information, basic data logged during the study, and proximity levels.

Participant	Gender	Age	Profession	Minutes Per Month	# Cell towers logged	% Phone off	%Arm's Reach	Proximity Category
1	M	24	Graduate Student	645	168	13	70	High
2	F	36	Homemaker	253	130	7	17	Low
3	M	46	Sales Rep.	4402	696	8	54	Med.
4	F	50	Graduate Student	344	253	10	45	Med.
5	M	41	Software Sales	1068	258	5	65	Med.
6	M	40	Mail Carrier	2905	269	6	51	Med.
7	F	47	Dry Cleaner	25	52	79	17	Low
8	F	23	Admin. Asst.	468	204	10	60	Med.
9	M	25	Consultant	559	139	1	84	High
10	M	61	Lecturer	384	414	12	47	Med.
11	F	21	Childcare Provider	1394	227	2	52	Med.
12	M	33	Project Manager	189	198	2	81	High
13	F	35	Homemaker	148	133	2	20	Low
14	M	32	Sales/Marketing	1769	900	32	44	Med.
15	M	66	Retired	984	227	2	35	Med.
16	F	24	Financial Associate	2075	254	5	51	Med.

4.5.2 Study Results

All participants successfully completed the study for at least three weeks. In every case, at least one of these weeks represented what they considered "typical" patterns, and in many cases, all three weeks were "typical." Participants reported the tag was comfortable to wear and did not interfere with their day-to-day lives. In some instances, participants reported forgetting to put on the tag first thing in the morning after leaving it off for sleeping. I adjusted to account for these errors. In this section, I present the results from both the automatically-collected proximity and phone context data and the self-reported results from the interviews.

4.5.2.1 Proximity Levels

Three levels of proximity between the user and the phone can be determined using the BlueTrack tag and application scheme. These are:

- Within arm's reach (within 1-2 meters of the tag)
- Within the same room (within 5-6 meters of the tag)
- Unavailable (beyond 6 meters from the tag)

From the minute-by-minute readings taken each day during the three-week study, I obtained between 6190 and 35791 proximity measurements, with an average of 1175 readings per day per person. When a phone was turned off, no proximity ratings can be logged, but the very nature of the phone being off indicates it is unavailable. Given the large quantities of data, I was able to analyze different scenarios that may or may not affect proximity. In this section, I report those scenarios that showed the most significant trends:

- In and out of the home (determined by cell ID)
- Waking vs. sleeping hours (determined by hours reported during interviews)
- Weekend vs. weekday (weekend being 12 AM Saturday to 12 AM Monday)

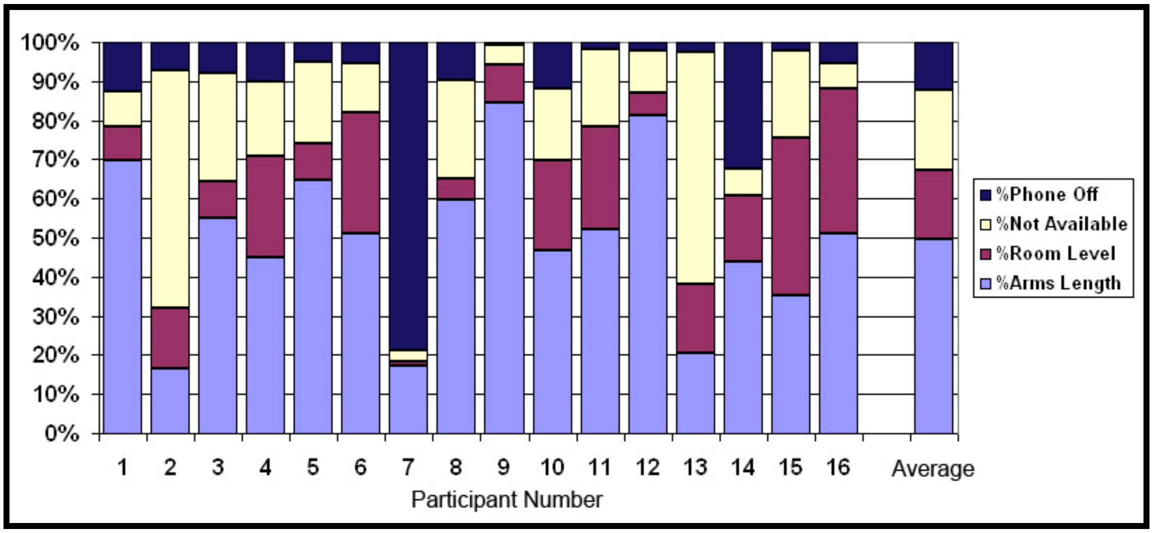
Overall, participants varied in their proximity levels, ranging from 17% of the time within arm's reach to 85% of the time, with an average of 58% of the time within arm's reach (see Figure 31). All but two users kept the phones on more than 85% of the time. Participant 7 had a prepaid plan and only had her phone on 21% of the time to conserve minutes, and Participant 14 turned his phone off almost every night while sleeping reportedly to avoid being disturbed.

Interestingly, participants showed a significant increase in the average percentage of time the phone was within arm's reach during times they were away from home ($p < 0.0001$; see Figure 31). Users were more likely to keep the phone at room level or even further while at home. In fact, the two participants with the lowest overall proximity data (2 and 13) were "stay-at-home" mothers who spent a significant time at home.

I compared proximity trends for individual users for times they were sleeping versus times they were awake. Participants had their phones within arm's reach more often while awake than they did while they were asleep (61% while awake, 52% while sleeping). Also, participants tended to keep their phones within arm's reach slightly more often on weekdays (59%) as opposed to weekends (53%). Although these values showed interesting trends, they did not demonstrate statistical significance.

The phone was within arm's reach and turned on, thus highly available, 50% of the time ($\sigma = 20.4$). Thus, I categorized users further than one standard deviation below the average (29.6%) as "Low" availability; users within one standard deviation as "Medium"; and users above one standard deviation (70.4%) as "High." Table 16 lists the proximity category. Contrary to the initial hypothesis, the number of minutes used per month on the phone does not correlate to the proximity relationship throughout the day. For example, the person with the highest number of minutes used per month, Participant 3, fits the Medium availability category. On the other hand, Participant 12 was highly available to the phone, but used it infrequently to make or to receive calls.

Other potentially correlating factors for proximity are age, gender, presence of a landline, and size of home or living space (see Figure 32 and Figure 33). These result indicate some trends, however, there were not enough participants to achieve statistical significance. As expected, individuals with larger living spaces tended to be farther from their phone than users with smaller living spaces. One possible reason for this may be that individuals charge their mobile phone while at home, thus making the likelihood of the mobile phone being on their person less likely. There was also a slight decrease in the proximity of the mobile phone for users that had another phone or landline at home. Males tended to have the phone within arms reach a larger percentage of the time than did females. One possible reason for this may be due to females keeping their phone in a purse, whereas the males in the study tended to carry their phone in their pocket or on a belt clip.



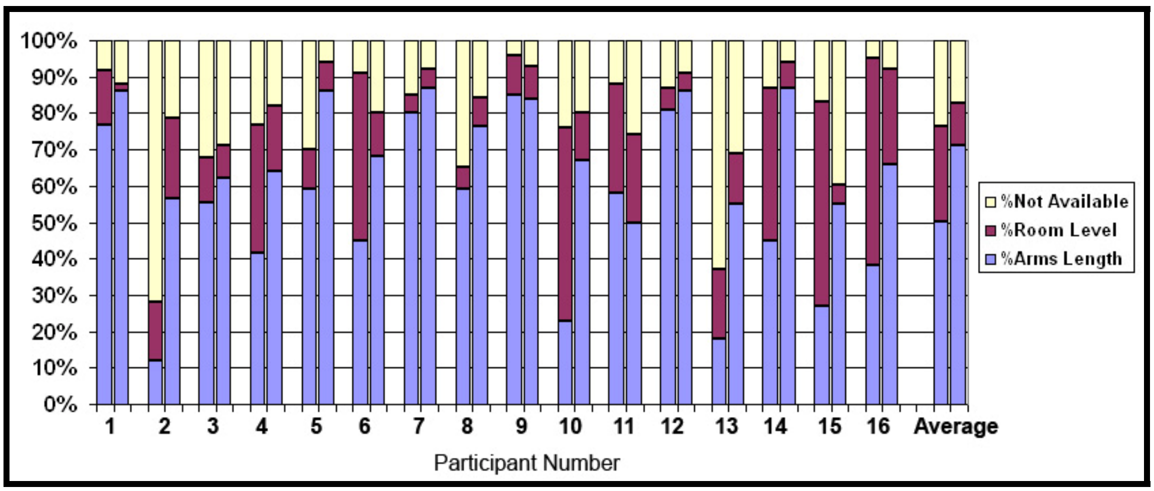


Figure 31: Individuals varied in proximity levels, but on average people kept their phone within arm's reach half the time (Top). Most users carried the phone close to them at all times when away from home if the phones were turned on (Bottom: Left bar is at home, Right is away).

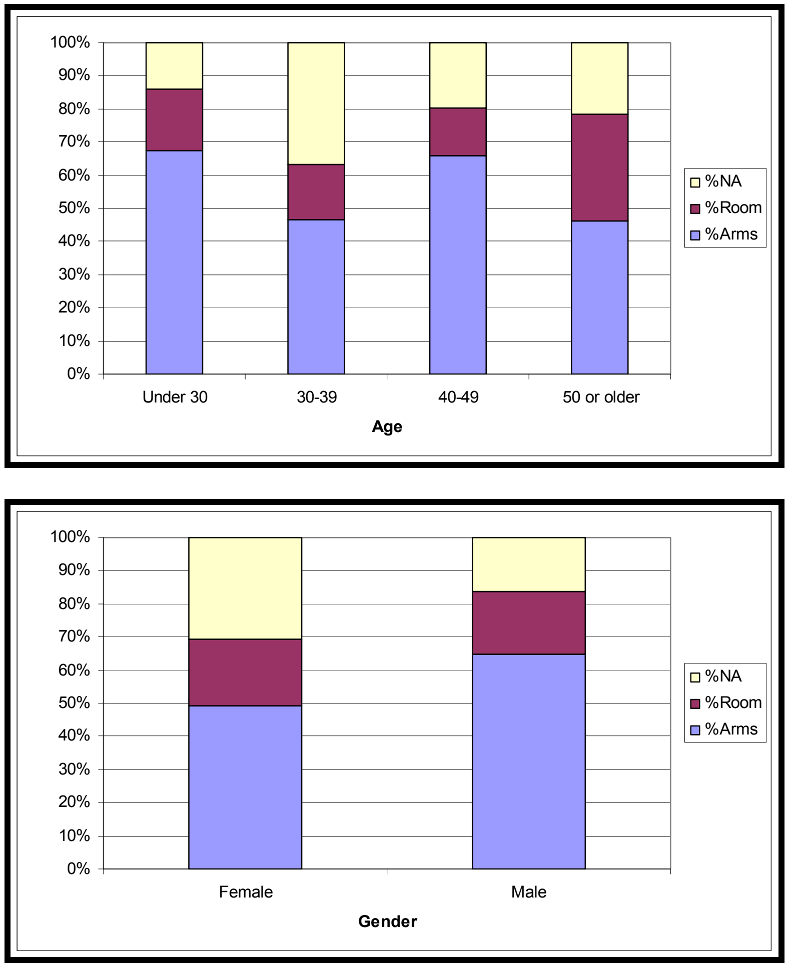


Figure 32: Proximity levels: a) according to age group b) based on gender

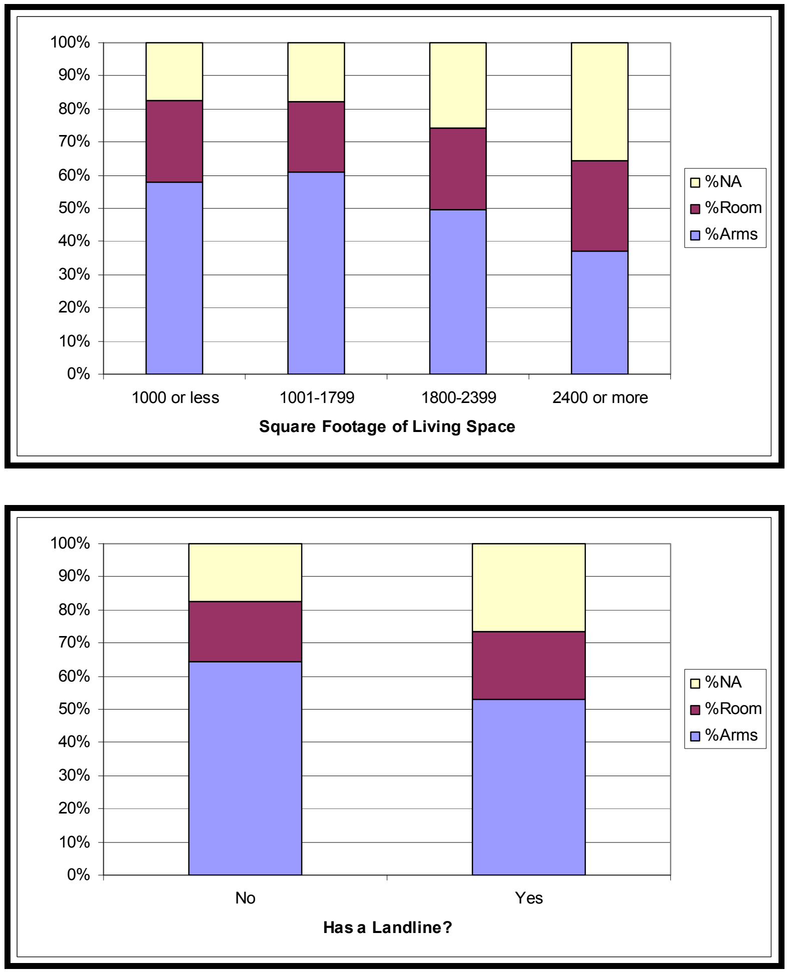


Figure 33: Proximity levels: a) while at home based on size of living space. b) while at home for users with and without a landline.

4.5.2.2 Factors Affecting the Proximity of Mobile Phones to Users

The weekly participant interviews served two purposes. First, during these interviews, participants described their own recollections of proximity to the phone. At times, their recollections and the automatically gathered data, visualized as in Figure 29, appeared to disagree. The interviews provided a time to discuss these discrepancies. Occasionally, participants recalled more accurate information about daily activities after being prompted by the automatically collected data. The interviews also provided an opportunity to note times that the tag was not an adequate proxy, typically because the participant could not wear the tag for some reason. For cases in which no resolution could be reached through the interview discussions, the discrepancy was attributed to technical error. These error cases always registered for only short time periods (a single data point) and occurred on average 3 times in a given day for a participant out of over 1200 data points each day.

Second, the interviews provided participants an opportunity to reflect on and explain activities grounded in the data, both automatically-collected and self-reported. These discussions resulted in better understanding of the factors that contributed to an individual's phone being near or not than would have been possible using solely the automatically-logged contextual information. These factors were determined in two ways: by examining the variables that most directly affected the learned model of the user and by using affinity clustering to group the self-reported reasons for the phone's proximity from the interview data.

Specifically, the affinity clustering results were produced by three researchers. The first recorded each participant's stated reasons for the phone's proximity and availability during the interviews. Two researchers then independently categorized these statements using affinity clustering to determine themes, producing 15 unique themes, 13 of which were shared. The two coders agreed on categorization of most of the cases (105 of 120), and after discussion, agreement was made to include all 15 unique themes. One of the original coders then re-categorized all of the statements while the third researcher categorized them independently using the 15 themes (see Table 17 for inter-coder reliability). The 15 emergent themes follow:

1. *Routine:* The phone's proximity is related to anything that is part of a common routine for the individual, particularly those things that might help them to remember the phone's location or be within range of its use. Example: User always leaves phone on kitchen counter while at home.

2. *Environment:* The phone's proximity is related directly to the distance at which the user believes the phone should be due to the physical constraints of the space. Example: In a car, the phone is rarely out of arm's reach.

3. *Physicality of person/Activity:* The phone's proximity to the user is related directly to something physical about the person or the activity in which he/she is engaged. Example: Phone is awkward to carry while working out.

4. *Disruption to others:* User makes a choice about the phone's proximity and/or on/off status based on how that choice affects other people or the environment. Example: User turns off phone during a client meeting.

5. *Disruption to self:* User makes a choice about the phone's proximity and/or on/off status based on that choice's effects on self. Example: User turns off phone at home after a long day of calls at work.

6. *Regulations:* Legal or other specific regulations prevent use, carrying, and/or powering of phone. Example: User has to turn off phone while in a hospital.

7. *Use of phone by self:* The phone's proximity is affected by the owner using it or anticipating use. Example: Phone is nearby while user is on a phone call.

8. *Need for use of phone by others:* The phone's proximity is affected by expectation that others may need to reach owner or otherwise make use of owner's phone. Example: Phone is nearby when the user is expecting a call.

9. *Need for use of phone both by self and by others:* The expectation of needing features for self as well as availability of self to others through the phone's features. Example: The user keeps the phone close while trying to coordinate a group of people at a social event.

10. *Use of handset by others:* Someone else is physically using the handset. Example: User loaned phone to spouse while she was out running errands.

11. *No need for use of phone:* Phone's availability directly affected by the belief that no use is imminent. Example: While at home, others can use a landline to reach the user.

12. *Technical resource issues:* The phone's availability and proximity are directly affected by technical considerations inherent to the phone or the network. Example: User moves close to a window to obtain a better signal or moves it to where the charger is located when the battery is low.

13. *Quick trips:* The timing (or expected timing) of an activity affects the user's choice about whether to explicitly consider/act on phone's proximity or not. Example: Phone is on the desk at work while taking a coffee break.

14. *Memory and forgetfulness:* Phone lost (at least temporarily) or unintentionally left behind due primarily to user's forgetfulness or memory error. Example: Phone is left behind while leaving the house.

15. *Protection of phone from others:* The user's choice about phone placement is directly related to protecting the physical handset or the resources that can be accessed through the phone from tampering or use by other people. Example: Phone on a high shelf out of the reach of children.

Table 17: Inter-coder reliability for each thematic cluster was determined using two measures: (1) Observed Agreement represents a measure of simple agreement between two coders for each theme and is measured by agreements divided by total number of statements coded; (2) Cohen's Kappa measures how much better than chance the agreement between the two coders is. Both range between 0 and 1, with 1 indicating perfect agreement between coders.

Cluster	1	2	3	4	5	6	7	8
Observed Agreement	.93	1	.99	.99	.98	1	.98	1
Cohen's Kappa (k)	.59	1	.83	.83	.81	1	.85	1

Cluster	9	10	11	12	13	14	15
Observed Agreement	.95	.99	.93	.99	.98	.99	.96
Cohen's Kappa (k)	.58	.91	.74	.75	.89	.95	.67

4.5.3 Predicting User's Proximity

The preceding section presents empirical findings on the proximity relationship as well as reasons for why a phone is not near its owner. An open question was whether this proximity relationship could be determined on the phone itself, without the aid of a proxy tag. I collected approximately 30,000 proximity readings per participant. In addition to proximity data, I also collected a variety of contextual data from the mobile phone. This information includes hour of day, day of week, cellular tower ID, cellular area ID, signal strength, battery level, charging status, ring volume, ring type or mode, vibration status, foreground application, idle status of the phone, missed calls, time and duration of incoming and outgoing calls, SMS messages, and GPRS data usage. I wanted to investigate whether the real proximity value could be deduced from some subset of those available data already on the phone and whether such a correlation was independent of the individual. If so, mobile phone application developers could create context-aware behaviors triggered by proximity.

The descriptive statistics and interviews summarized throughout this paper suggest that some features do have predictive power. For example, for participants with very structured work schedules, day and hour were effective features for predicting proximity to the phone. Cell tower IDs and charging status were two other contextual features that also showed promise. Many of the participants tended to have their phones on their bodies every time they were away from the cell towers near their homes. Some people only charged their phones while in the car, which made using the charger status (*i.e.,* whether or not connected to charger) one method of inferring that those users would be arms-length from their phones at those times. Figure 34 shows evidence of patterns existing between features and the user's proximity to their phone.

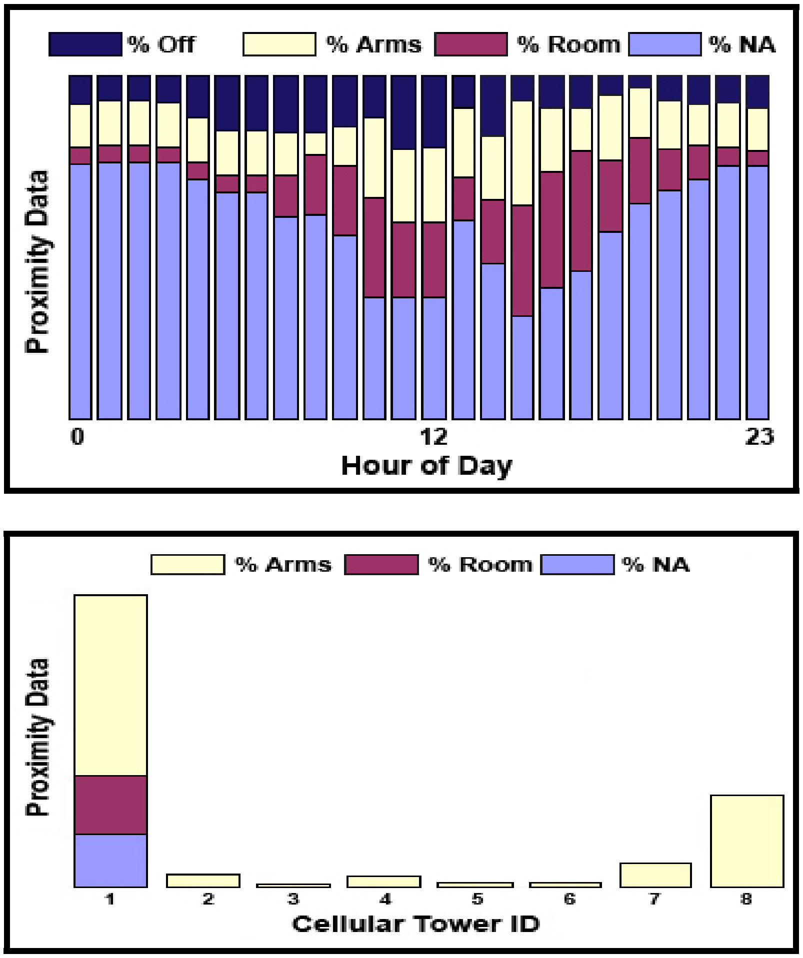


Figure 34: Left: Proximity percentages for each hour of the day for Participant 2 (a homemaker). Right: Proximity percentage for each cellular tower ID, again for Participant 2. Cell ID #1 is the participant's home and is the only one that has variability on proximity level.

4.5.3.1 Proximity Classifier

From a machine learning perspective, the real question is whether the features that predict proximity were general across individuals. I created a model that could classify and predict the proximity of an owner to the mobile phone based on the logged contextual features. I employed a decision tree classifier using the ID3 algorithm [81]. Decision trees have several important advantages for my aim as compared with classifiers such as neural networks, support vector machines, or boosting methods. First, they are lightweight yet effective predictors that can function on a mobile phone. Second, the internal representation of a decision tree is highly human-interpretable and thus can inform application design decisions. Furthermore, a decision tree built with the ID3 algorithm doubles as a feature selection mechanism. ID3 works by greedily applying an information gain criterion for selecting which features to use for prediction. Thus, the features near the root of the tree have high predictive power and can be thought of as the most important features. Therefore, the initial question of whether there are common features of significance across all individuals can be addressed by determining whether the root of the decision tree varies across users and, if so, how.

This challenge can be formulated as a supervised learning problem, in which the class labels are the three levels of proximity, and each instance is a feature vector encoding the logged contextual information. I first tested the performance of the decision trees by using all three weeks of data for each user. I used 10-fold cross-validation to ensure effective use of the entire data set without biasing the test phase. To ascertain how many weeks of training were actually necessary for high accuracies, I conducted tests using restricted training sets. In one test, I used the first two weeks of data for the training set and the third week for the test set. In the second, I used the first week of data for training and the other two weeks as the testing set.

As a baseline, I compared decision trees against a majority classifier to demonstrate how much additional predictive power a decision tree actually provides (see Table 18). On average, the decision tree classifier ranged in accuracy from 85-90%. The subjects with high majority classification accuracies tended to be arms-length from their phones for significant periods; however, the prediction accuracy still improved when using decision trees. For subjects with an even distribution among the three proximity levels, the majority classifier performed poorly, as expected, and the decision trees dramatically increased the accuracy. Reducing the training set down to one week still provided classification accuracies between 84-88%, suggesting that one week of training is sufficient to provide near-optimal prediction accuracies.

Table 18: Classification accuracies in percentages. The test using 3 weeks of data was conducted using 10-fold cross-validation over the entire data set.

Participant	Majority Classifier	Tree: 3 wks training	Tree: 2 wks training	Tree: 1 wk training	Tree: cell id, hour, & day	Tree: the top 4 features
1	77.0	90.1	89.2	87.7	85.0	88.1
2	53.6	88.9	87.2	85.8	80.2	86.5
3	59.4	93.1	88.0	85.8	78.4	85.4
4	49.8	86.1	85.1	84.0	85.8	86.0
5	68.3	85.0	83.7	82.9	73.5	82.5
6	53.8	86.3	85.9	85.1	79.2	84.0
7	81.5	90.1	90.0	88.2	90.0	90.0
8	65.9	88.7	87.9	86.5	82.1	85.3
9	84.6	91.0	90.8	89.4	88.1	88.9
10	52.4	90.1	89.2	88.3	86.6	88.5
11	52.8	84.1	82.6	80.9	82.4	83.9
12	83.1	89.6	86.8	84.4	84.8	87.4
13	60.5	85.6	84.3	84.2	75.2	82.8
14	64.7	87.4	85.2	84.8	84.0	85.6
15	40.7	87.3	86.9	85.3	83.8	86.1
16	53.6	90.1	89.4	89.0	84.4	87.5
Averages	**62.61%**	**8834.38%**	**8701.25%**	**8576.88%**	**8271.88%**	**8615.63%**

4.5.3.2 Analyzing the Decision Trees

I analyzed the decision tree for each of the 16 participants and determined the most important features for classification (see Table 18). For every subject, either cell tower ID, hour of the day, or day of the week was the root node (*i.e.*, the most predictive feature). These three features also appeared in the top four contributing features for each subject. Depending on the user, the remaining best feature was one of signal strength, charger status, or ring/vibrate status. To test the power of these top features, I calculated the decision tree accuracies for each subject using only their top four features (see Table 19). Restricting the feature set to only the top four features does not result in a large decrease in accuracy. I also computed the classification accuracies using only the cell tower ID, hour, and day features for each subject and observed an average accuracy of 83% (an average accuracy loss of 5%). Thus, comparable classification accuracies can be obtained with a common set of minimal features, meaning I do not even need to have a training phase in practice.

Time and location are major factors for predicting user proximity to a mobile phone. Participants with hour or day as their top feature typically had structured workdays in which they interacted with the phones in a consistent pattern. For some users, the ring or vibrate status was a good indicator for proximity to the phone. The phone being within arm's reach often correlated to the acts of disabling the ring volume and activating the vibrator. On the other hand, a high ring volume often correlated to the phone being distant from the user. Many users typically carried the phone very close to them when they were away from home, as determined by cell tower IDs. Charger status and signal strength may have provided some subtle location information as well. For example, participants that only charged the phone in the car were very likely to be within arm's reach of the phone during charging. Users that only charged at home tended to be further away from the phones during charging. Often, the signal strength branched from cell tower IDs in the decision trees, indicating that the signal strength was playing a disambiguating role in those cases.

Table 19: This table shows that three groups of users emerged based on their top four features. Note that I present the features in no particular order of predictive power.

% of Participants	Feature 1	Feature 2	Feature 3	Feature 4
19	Cell ID	Hour	Day	Ring/Vibrate
50	Cell ID	Hour	Day	Charger
31	Cell ID	Hour	Day	Signal

4.5.4 Discussion

BlueTrack allowed me to obtain realistic proximity data for users that may not have otherwise been obtained with more low fidelity studies. Although a sampling of data points obtained through ESM can come up with similar proximity relationships, it runs the risk of altering the user's proximity relationship to the phone by continually reminding users about their phones' whereabouts. Based on interviews with all the participants and analysis of the proximity data there was little modification to user's natural behavior during the study. They also reported no discomfort with the location tag and often reported "forgetting about it" soon after wearing it.

Additionally, resulting quantitative proximity traces proved valuable during the interview process. This resulted in much richer interviews that focus on more specific details than in generalities. As a result, it was possible to uncover various categories of separation that the users would not have remembered or thought to report. In addition, often participants could not recall the location of their phone. Thus, the proximity traces proved vital for the participants when they were explaining particular situations.

Finally, the objective proximity data showed that participants are not good at predicting their physical relationship to their mobile phone. Most participants grossly overestimated the mobile phone being close to them. The continual logging with BlueTrack also provided substantial data for creating a model to predict a user's proximity to their phone and helped discover contextual features off the phone that contributes to this prediction.

I believe this type of study is useful to obtain ground truth data about a user's proximity relationship to the phone. Perhaps more significantly, however, it can also result in baseline data to compare against similar proximity evidence that would result from the effects of new mobile phone applications, such as location-based services, continual health monitoring systems, or context-aware applications, will have on that proximity relationship. Finally, this same technique may be used to evaluate proximity relationships between collections of mobile phones and their owners as well as the proximity relationships between people and other technologies, mobile or stationary.

4.5.4.1 Potential Alternative Data Gathering Methods

I considered several different methods of data collection when designing this experiment. In addition to the constant logging method, I considered conducting an experience sampling method (ESM), such as that used by Consolvo and Walker [22], or using solely self-reported data via a diary study, surveys, or interviews. I did not believe that self-report would provide the fine-grained, accurate information I needed, and when conducting the actual study, I observed that individuals often could not even accurately report where the phone was in the past day, even though they could remember the episodes of the day clearly.

Diary studies would likely have required too much work from the participants to get a broad range of samples. ESM, on the other hand, might have been appropriate, but I was concerned that random sampling would not uncover the subtle details inherent to user habits with mobile phones. To test this hypothesis, I randomly selected 16 data points per day (1 per hour) from each participant (one probe per waking hour) and calculated the average proximity level for each participant. I calculated this average for 100 random samplings and an overall average was calculated (see Table 20). The simulation assumed participants would be willing and able to respond to 16 queries per day for a three-week period. The percentages provided by the simulations were close to the actual data for most participants, despite only having 16 samples per day, compared to 1440 per day for the empirical study.

Although the overall percentages were similar, the ESM data would not include some of the more fine-grained details I was able to harvest from the high resolution, automatically-collected data, including times when the user was away from their phone for a short period. For example, I calculated the number of times per day each person was away from his or her phone for a short amount of time (2-20 minutes), *i.e.*, a “quick trip” as defined above. The participants each reported from 1 to 20 of these quick trips away from the phone per day. This information could be crucial to applications on a phone that assume the user is nearby all the time, such as reminder systems or constant health monitoring. Furthermore, with a sampling method, overall trends in some of the other features, such as phone call usage and number of cell towers detected by the phones would likely be missed. Lastly, and possibly most importantly, the empirical study did not require users to be conscious of their phone's location at all times, thus allowing me to capture a more realistic data set.

Table 20: Comparison of empirical proximity data to percentages from a simulated ESM study.

Level	Overall Empirical	Overall ESM	Weekend Empirical	Weekend ESM	Weekday Empirical	Weekday ESM
Arms	58	61	53	55	59	64
Room	20	14	18	13	20	15
NA	23	24	28	32	21	21

4.5.4.2 Design Considerations for Mobile Devices

The empirical results allowed me to begin to uncover some interesting insights for mobile phone application designers to consider. Mobile phones may not be as good of a location proxy as many people believe. The participant with the closest overall proximity level was within arm's reach of his phone 85% of the time, despite his strong intuition that he carried the phone nearly 100% of the time. Certain features, such as the number of minutes of "talk time" are not as good predictors as intuition might have us believe. When considering a particular group of users, designers can leverage simple information available on the phone itself (time and location) to infer a user's proximity to the mobile phone. When away from home, the phone is more likely to be with the individual. Thus, designing applications for use in home would need to make different assumptions about a mobile phone's proximity than those for outside the home.

The effect of physical activity on participant choices about phone proximity is an indicator that those potential applications that focus on monitoring of physical fitness activities should consider the physical reasons users might avoid carrying a phone during these periods in designing their form factors. As expected, users keep their phones near in the presence of perceived needs. Thus, one solution for applications that require the user and phone being close most of the time is to build in functionality that the users may need regularly. Control over disruptions is important to users. Thus, any applications relying on interruptions must consider social, regulatory, and personal reasons for minimizing disruptions.

4.5.4.3.1 *Applying Guidelines to Example Applications*

I show how the findings can inform the design of some example applications that rely on the mobile phone as a proxy for the individual. I apply these guidelines to two previous research applications: The Personal Audio Loop (PAL), a near-term audio reminder system, and Reno [24], a social location disclosure application.

PAL is a mobile phone application that continuously records a buffer of near-term audio and allows the user to quickly replay audio to assist the user in recalling a conversation in the event of an interruption or a lapse in memory. There are interesting concerns in the development of this type of memory device, many of which are rooted in assumptions about the proximity relationship between the user and the PAL device. For example, PAL provides "always on" recording of the environment local to the mobile phone, assuming that this area includes the individual's own private communication space. There is the option of transferring recording duties to the surrounding environment when the mobile phone is not near the user. The important questions are then: *When and where is the mobile phone in microphone range to the user? When the phone is out of range, is the user in a location where an environmental version of PAL is feasible?*

Based on the results, the availability of a mobile phone is more likely in a car and away from home, where users tend to be closer to their mobile phone. Since it is very difficult to instrument all of the physical space that a person may inhabit, the mobility of PAL is important. When users are away from their home or their primary work spaces, the mobile phone is in microphone range a large portion of that time. However, this is not the case when users are at home or sometimes at work. The phone tends to be in a single location and out of microphone range. The size of one's living space also contributes to this problem. In addition, it is also inconvenient to retrieve the phone when it is not nearby, and there is need for the use of PAL. This argues for an environmental version of PAL, such as leveraging microphones built into telephone speakers, intercom systems, personal computers, or laptops. The proximity prediction on the mobile phone can serve as a trigger for activating an environmental system.

There are other compelling reasons to want to study and to better understand the "phone as location proxy" assumption. For instance, in an age of increasing digital capabilities, there are legitimate concerns by individuals who want to retain control of what information is recorded about them. In the example of PAL, some preliminary studies indicate that while individuals are comfortable with others keeping recordings of their prior conversations, they would want to authorize such recordings in advance [8]. If and when the mobile phone is a suitable location proxy for an individual or a group of individuals, one can consider the design of recording policies that the phone can enforce on behalf of its owner, providing a possible balance between control and management of a large number of such requests throughout the day. For instance, by automatically inferring the proximity of the mobile phone, PAL can automatically disable its recording if the phone is left unattended or is away from its owner. In addition, the proximity estimation can be used to modulate the effective range of the microphone to mitigate problem of recording distant bystanders.

The second application one can apply these findings to is Reno, a social location disclosure application that allows the simplified exchange of location information between family and friends. Reno is based on Place Lab, an effort to provide ubiquitous location information on commodity devices. Recent findings have shown that GSM-enabled mobile phones can provide a ubiquitous location service with accuracy within 4-5 meters, but there is an implicit assumption that the phone is near its owner. Designers can improve applications like Reno with a better understanding of when and where that proximity assumption holds.

It is clear that the original design for Reno is sufficient based on the results of this study. The key use of Reno is when individuals are mobile and away from home, where most users tend to have the phone on or near their person for significant portions of the day. For example, times when a person may leave the phone unattended for a short period is not detrimental to the success of Reno, since much of its use is not time critical. When the user is at home, where a majority of the users did not have their phone next to them, the mobile phone can infer that the individual is at home and automatically reply to Reno messages. Lastly, the proximity prediction could be used by Reno to automatically notify authorized individuals that the person is away from the phone or route the message to a different device.

4.5.4.3 The Value of Proximity Modeling

A small number of features can predict the likelihood of proximity with fairly high confidence. Some of these features are the same across all participants, such as cell tower ID, hour and day, and together yield 83% predictive power. The ease of sensing these features on a mobile phone and the availability of lightweight machine learning techniques suggest that it is possible to build a context-aware mobile phone that can predict relatively easily the user's proximity to the phone. Such a system is valuable for applications that rely on the mobile phone as a proxy for a user, because it would allow for appropriate adaptation to situations in which proximity is a concern.

Central to the development of such a system is the model of the individual user. A simple tagging scheme, such as the one used for this study, can result in an accurate model with one week of "typical" use. However, this tagging method may not be practical for everyone. Thus, creating predefined or easy to construct models *a priori* for particular types of mobile phone users is an important consideration for effective adoption of this kind of system. Having identified common features across users and categories of user with respect to these features, I believe it possible to devise a survey mechanism in which users answer high-level questions. The answers to these questions could then translate into low-level modeling information to form the basis of a proximity-aware mobile phone.

4.6 Overview of Contributions

- The design and creation of a three-level proximity-sensing technique based on low-cost Bluetooth technology that does not require the active paring between devices
- Technical evaluation of BlueTrack
- Demonstration of the value of automatic logging compared to other investigational methods
- Design and execution of an empirical proximity study of mobile phones to their users that used the BlueTrack system
    - I presented empirical evidence directly testing the strength of the assumption that the mobile phone is a good proxy for its owner's location.
    - I presented a classification of situations that break the proximity assumption, information that can be interpreted as design advice for mobile phone applications.
    - I presented a decision tree method for predicting proximity to mobile phones based on readily accessible features on the phone itself.
    - I provided a baseline measure that other researchers can use as a basis for comparison to when deploying new mobile phone applications.

CHAPTER 5

A NEW GENERALIZED APPROACH TO ACTIVITY SENSING: INFRASTRUCTURE MEDIATED SENSING

In this chapter, I present a generalization of the two sensing systems presented in Chapters 3 and 4, called *Infrastructure Mediated Sensing (IMS)*. To overcome the challenge of obtaining human activity data in a widely deployable approach, IMS enables practical installations of sensing in a home for location and activity sensing. I will also discuss additional IMS-based activity sensing systems.

5.1 Infrastructure Mediated Sensing

I contend that there are two ways to distinguish between sensing approaches. One is the distributed direct sensing (DDS) approach and the other is the newly described category, infrastructure mediated sensing (IMS). Distributed direct sensing involves the installation of a completely new sensing infrastructure into the home. This sensing infrastructure directly senses the presence, motion, or activities of people through sensors that are physically located in each space where activity is occurring. Example systems include a new set of sensors and data connections to transfer the sensor data to a centralized monitoring system where sensor fusion and activity inference take place. In contrast, infrastructure mediated sensing leverages existing home infrastructures, such as the plumbing or electrical systems, to mediate the transduction of events. In these systems, the infrastructure activity is used as a proxy for human activity involving the infrastructure (see Figure 1). In addition, the infrastructure can be used to send custom probes through the environment without the need of addition new hardware, such as in the case of PLP. The advantages of IMS-based systems are the reduction in cost, installation time, and maintenance time of complex sensing systems.

Most of prior work in human activity sensing in the home falls into the distributed direct sensing category (see Chapter 2). In the ubiquitous computing research context, commonly used sensors for detecting human activity in the home include high-fidelity sensors such as visible light and IR cameras or microphones, as well as low-fidelity sensors such as passive infrared (PIR) motion detectors and floor weight sensors. High-fidelity distributed direct sensing has a long history of use in activity detection and classification research, primarily focused on computer vision or machine learning systems that capture the movement of people in spaces. For example, researchers have looked at installing microphones in a bathroom to sense activities such as showering, toileting, and hand washing. The use of these high fidelity sensors in certain spaces often raises concerns about the balance between value-added services and acceptable surveillance, particularly in home settings. Low-fidelity, distributed direct sensing work includes the use of a large collection of simple, low-cost sensors, such as motion detectors or contact switches, to determine activity and movement.

All distributed direct sensing approaches share the advantages and disadvantages of placing each sensor in close proximity to where human activity occurs. For example, commonly used cameras or PIR sensors require a clear line of sight to the desired room coverage area; the person being sensed will be able to see the camera or PIR sensor. Generally, cameras or PIR sensors are deployed in places that have adverse aesthetics, such as on walls, on ceilings, or above a door. The large number of sensors required for coverage of an entire building presents an inherent complexity hurdle. Installation and maintenance of (typically) tens of sensors in a home, or hundreds to thousands of sensors in a larger building such as a hotel, hospital, or assisted living facility, results in high labor costs during installation, and an ongoing maintenance and sensor network management challenge during routine operation.

It is often difficult to balance the value of in-home sensing and the complexity of the sensing infrastructure. One example that illustrates this difficulty is the Digital Family Portrait system, a peace-of-mind application for communicating well-being information from an elderly person’s home to a remote caregiver [112]. In the system's deployment study, movement data was gathered from a collection of strain sensors attached to the underside of the first floor of an elder’s home. The installation of these sensors was difficult, time-consuming, and required direct access to the underside of the floor. Though the value of the application was proven, the complexity of the sensing limited the number of homes in which the system could be easily deployed.

Some recent innovative work in the infrastructure mediated sensing category leverages the existing infrastructure in a home to collect signals at a single location. A few researchers have recently begun exploring the use of existing home infrastructure to detect human originated events [36, 100, 101, 102]. A few microphones on the plumbing infrastructure in the basement of a home can infer basic activities, such as bathing or washing dishes, through acoustically-transduced signals [36]. A single plug-in sensor can classify events, such as the actuation of a light switch, through the analysis of noise, transduced along the power line, from the switching and operation of electrical devices [101]. These two approaches cover a complementary set of human activities, depending on whether a water- or power-related event precedes that activity. Both of these approaches require human-initiated events, as identified through signals carried via the infrastructure of their corresponding resources, in order to provide human activity information.

I contrast infrastructure mediated sensing with a "piggybacking" approach that simply reuses an existing sensing infrastructure in the home that may be present for other purposes. For example, ADT Security System's QuietCare [3] offers a peace-of-mind service that gathers activity data from the security system's PIR motion detectors. Although a promising approach, security motion sensors are typically only installed in a few locations in the home, primarily on the ground floors, resulting in a much sparser dataset than is needed for general activity recognition.

I have identified the home electrical system, plumbing system, heating, ventilation, and air conditioning (HVAC) system, natural gas piping, and computer network (whether wired or wireless) as widely deployed, existing infrastructure buses where initial experiments have shown that we can sense human generated events caused by interaction with those buses.

5.2 Advantages and Challenges of IMS

There are several important distinguishing features between DDS and IMS, as shown in Figure 1. Distributed direct sensing involves the installation of a new sensing infrastructure into the home. This sensing infrastructure directly senses the presence, motion, or activities of its residents through sensors that are physically located in each space where activity is occurring. In IMS systems, infrastructure activity is used as a proxy for a human activity involving the infrastructure. Thus, by leveraging the existing infrastructure for the purposes of sensing, it is possible to greatly reduce the deployment burdens associated with sensing systems.

There are three primary advantages of the IMS approach as compared to the existing DDS approach. First, IMS leverages the existing infrastructure of the home both for transducing human generated events (*e.g.,* turning on a light switch or opening a plumbing faucet) and for carrying that transduction to a central point (*e.g.,* the home electrical panel or water entrance pipe). The purchase and installation of new, dedicated human activity sensors, or a separate network to carry sensor data, are not required.

Second, endpoints for multiple IMS transduction modalities are already distributed throughout most homes. In a typical home, every room has electrical outlets and HVAC ductwork (in homes with central heating), while kitchens and bathrooms have widespread plumbing installed. There is no need to install or maintain a separate set of sensors to provide a dense sensor infrastructure. The aesthetics of the home are not impacted because the buses can be monitored from hidden "bus taps".

Finally, because the IMS buses are considered essential parts of the home, the home's occupants already perform failure detection and maintenance. Failure of the electrical or plumbing system is likely to be noticed immediately, and professionals such as electricians and plumbers are well-trained to diagnose problems with the infrastructure and to repair it when needed.

There are some important challenges to be overcome, however, before IMS can be proven as a viable research tool as well as a candidate sensing technology for widely deploying activity aware applications. IMS, when used alone, can only be used to detect human activities that have a measurable effect through the production of bus events on the observed buses. Not all human activities produce a direct effect on the bus, and not all buses will provide useful input at every moment in time. For example, sleeping may be indistinguishable from being out of the house from the point of view of a sensor on the plumbing bus. I expect that this issue can likely be mitigated by the introduction of a human activity model and activity recognition to account for the lack of a 1:1 correspondence between human activities and bus events. The optimal form of this model depends on the combination of buses being observed, and this is an important underlying research question to be answered by the proposed research.

IMS relies on the reuse of buses and endpoints that are not designed to be sensors and data transmission networks. The IMS approach requires the use of secondary effects, such as electrical noise produced by the transient switching of lighting or noisy electronic appliances and released back onto the electrical bus. These secondary effects are not the primary function of the bus endpoint, so they are not well controlled from unit to unit. This has both benefits and drawbacks, because IMS relies on this variability to discriminate among endpoints even though they are not designed to present a unique "signature" to the bus. The bus itself is a passive transmission line; it does not contain an engineered collision avoidance strategy to prevent two bus events from occurring at the same time and masking each other. Another important underlying research question is the stability and predictability of endpoint signatures in both the short term (day-to-day) and over the long term, since the lifetime of a faucet or an electrical appliance may span many years.

Because of the *a priori* unpredictability of endpoint IMS signatures, a robust training and machine learning framework is required to learn the signature of different endpoints, learn the layout of the buses, and to differentiate among these signatures when buses are in operation. Because of the large number of different endpoints in a typical house, the noisy source separation problem is likely to be challenging. Additionally, the training problem presents an important challenge. The tradeoff between the size of the training data set and the accuracy of event classification will again depend on the precise combination of IMS buses and the properties of the endpoint devices on each bus. The amount of training data required will in turn affect consumer acceptance of the IMS approach.

Finally, the IMS approach does not have the inherent spatial localization of sensing areas present in the DDS approach. One of the most important benefits of the DDS approach lies in its spatially distributed nature. Because of the inherent locality of human activity and sensor transduction in the DDS approach, trustworthy spatial information is available directly from the known sensor location. In contrast, in the IMS approach, spatial location is part of the machine learning task. Part of the training process is to spatially separate endpoint devices and to map these devices to physical space in the home. Time domain information can help with this mapping, since most buses have characteristic propagation delays, but these delays are not generally known a priori.

5.3 PowerLine Event Detection: Leveraging Existing Power Lines

Inspired by the IMS theme of leveraging existing infrastructure to support activity detection, PowerLine Event Detection is an approach that uses the home's electrical system as an information source to observe various electrical events. The detection and classification of these events can be used later for a variety of applications, such as healthcare, entertainment, home automation, energy monitoring, and post-occupancy research studies. A principal advantage of the approach is that it requires only the installation a single, plug-in module that connects to an embedded or personal computer. The computer records and analyzes electrical noise on the power line caused by the switching of significant electrical loads. Machine learning techniques applied to these patterns identify when unique events occur. Examples include human-initiated events, such as turning on or off a specific light switch or plugging in a CD player, as well as automatic events, such as a compressor or fan of an HVAC system turning on or off under the control of a thermostat.

By observing actuation of certain electrical devices, the location and activity of people in the space can be inferred and used for applications that rely on this contextual information. For example, detecting that a light switch was turned on can be an indication that someone entered a room, and thus an application could adjust the thermostat to make that room more comfortable. It can also detect other human-initiated kitchen events, such as a light turning on inside a refrigerator or microwave when its door is opened. The combination of these events may indicate meal preparation. My approach also has implications for providing a low-cost solution for monitoring energy usage. An application could log when particular electrical loads are active, revealing how and when electrical energy is consumed in the household, leading to suggestions on how to maintain a more energy-efficient household. In addition, because the approach is capable of differentiating between the on and off events of a particular device in real time, those events can be “linked” to other actuators for a variety of home automation scenarios. One can imagine a home automation system that maps the actuation of a stereo system to an existing light switch without having to install additional wiring.

In this section, I describe the underlying theory and initial implementation details of the approach to PowerLine Event Detection. I report the results of a series of tests to determine the stability of the approach over time and its capability of sensing electrical events in different homes. These tests consisted of installing the device in a single location of a house and collecting data on a variety of electrical events within that house. Results show the support vector machine system can learn and later classify various unique electrical events with accuracies ranging from 85-90%. Finally, I discuss the results, current limitations, and potential improvements for this PowerLine Event Detection approach.

5.3.1 The Approach and System Details

The prototype system consists of a single module (see Figure 35) that is plugged into any electrical outlet in the home. Although not necessarily required, I installed it in a convenient, central location in the home while experimenting with the setup. The other end of the plug-in unit is connected via USB to a computer that collects and performs the analysis on the incoming electrical noise. The system learns certain characteristics from electrical noise produced by switching an electrical device on or off and later predicts when those devices are actuated based on the learned phenomena. Note that I present an approach for countries that use 60 Hz electrical systems, but the approach can easily be extended to different frequencies used in other countries (*i.e.*, those that use 50 Hz).

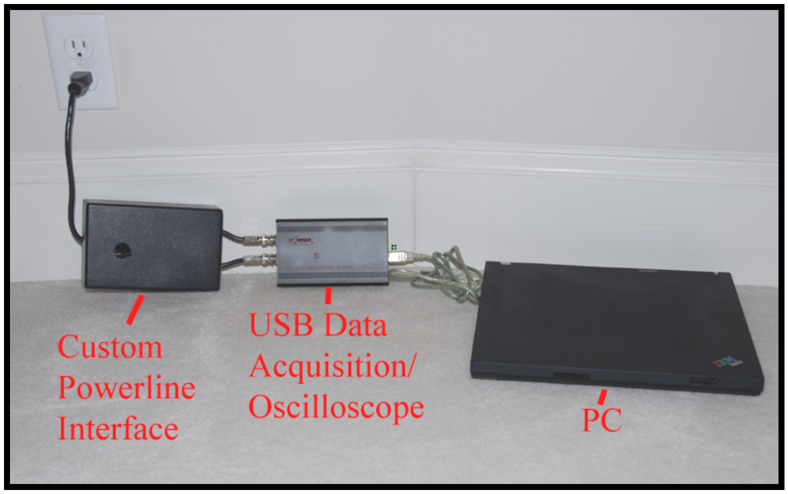


Figure 35: The prototype system consists of a powerline noise analyzer plugged in to an ordinary wall outlet and connected to a PC.

5.3.1.1 Theory of Operation

My approach relies on the fact that abruptly switched (mechanical or solid-state) electrical loads produce broadband electrical noise either in the form of a transient or continuous noise. This electrical noise is generated either between hot and neutral (known as normal mode noise) or between neutral and ground (known as common mode noise). Transient and continuous noise on the residential power line is typically high in energy and may often be observed with a nearby AM radio. The types of electrical noise in which I was interested are produced within the home and are created by the fast switching of relatively high currents. For example, a motor-type load, such as a fan, will create a transient noise pulse when it is first turned on and will then produce a continuous noise signal until it is turned off. In addition, the mechanical switching characteristics of a light switch itself can generate transient electrical noise [52]. Other examples of noisy events include using a garage door opener, plugging in a power adaptor for an electric device, or turning on a television. Marubayashi provides a more complete description of this electrical noise phenomenon [74].

In the case of transient noise, the impulses typically last only a few microseconds and consist of a rich spectrum of frequency components, which can range from 10 Hz to 100 kHz. Thus, it is interesting to consider both the temporal nature (duration) of the transient noise and its frequency components. Depending on the switching mechanism, the load characteristics, and length of transmission line, these impulses can be very different. For example, Figure 36 shows a sample frequency domain graph of a light switch being toggled in a house (light on followed by light off). Note the rich number of high amplitude frequency components for each pulse and their relative strengths. Also, notice that the signature of a device being turned on is different from the same device being turned off. Figure 36 shows the same switch being actuated in the same order, but taken 2 hours later, and shows it taken 1 week later. The amplitudes of individual frequency components and the duration of the impulse produced by each switch are similar between the three graphs, although there are a few high frequency regions that are different across the samples. Even similar light switches produce different signatures, which is likely due to the mechanical construction of each switch and the influence of the power line length connected to each switch. For example, I observed that three-way wall switches connected to the same light each produced discernable signatures. The main difference was in the relative amplitudes of the frequencies being observed. For devices that produce continuous noise, they are bounded by some transient phenomena, but also exhibit electrical noise during their powered operation. For this class of noises, it is possible to not only identify it based on its transient response but also its continuous noise signature.

Because I assume the noise signature of a particular device depends both on the device and the transmission line behavior of the interconnecting power line, I have attempted to capture both contributions in a single model. Figure 37 depicts a high-level overview of the simplified model of a home's electrical infrastructure and where particular noise transfer functions occur, denoted as H(s). These transfer functions reflect the expectation that both the electrical transmission lines and the data collection apparatus connected to that line all contribute to some transformation of the noise from the source to the collection apparatus. The observed noise results from the imposition of all the transfer functions against the generated noise. The influence of the transmission line’s transfer function is an important contributor to the different electrical noise signatures I observed, which explains why similar device types (*e.g.*, light switches) can be distinguished and why the location of the data collection module in the house impacts the observed noise.

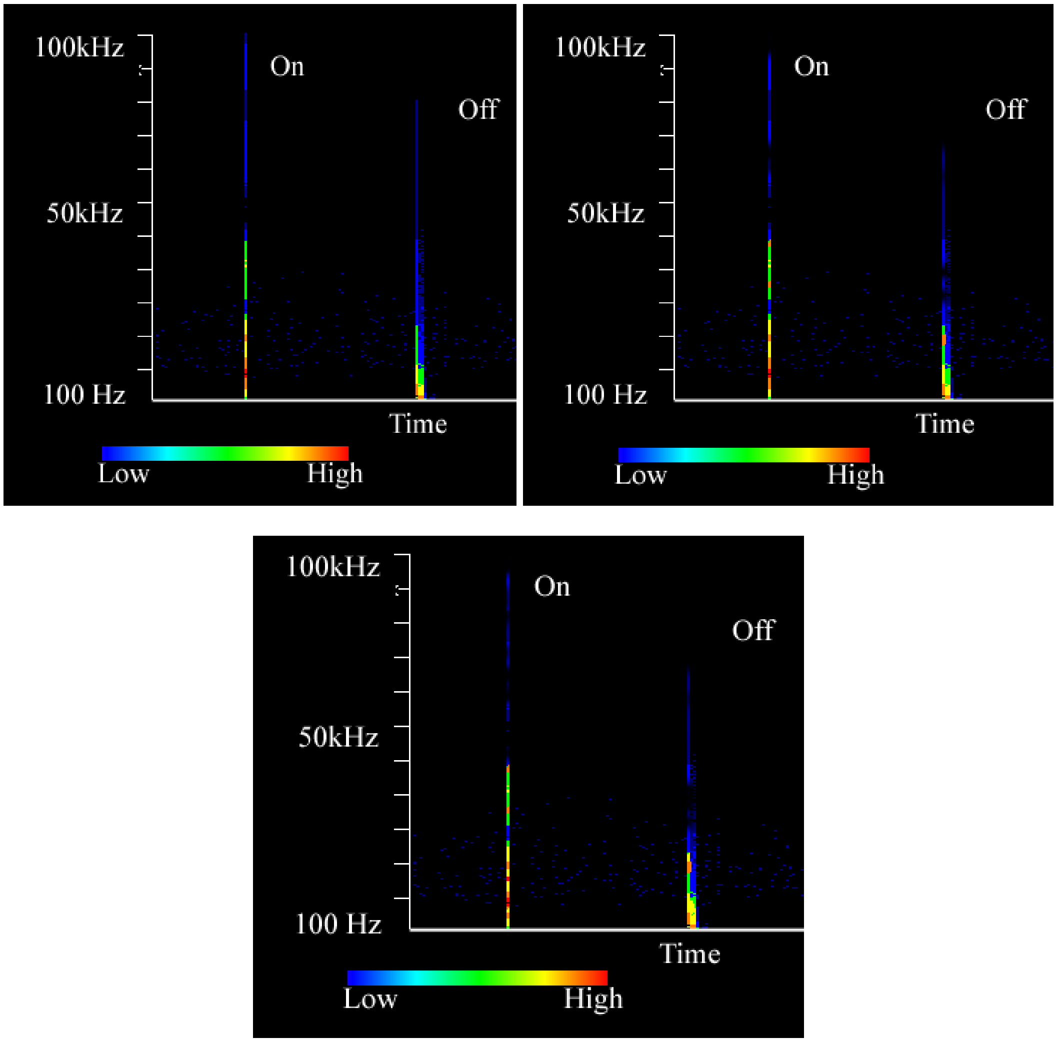


Figure 36: Frequency spectrum of a particular light switch being toggled (on and off events). The graphs indicate amplitudes at each frequency level. Events in (b) were captured two days after (a), and events in (c) were captured one week after (a). Each sample is rich in a broad range of frequencies. On and off events are each different enough to be distinguished. In addition, the individual on and off events are similar enough over time to be recognized later.

In the simplified model, three general classes of electrical noise sources may be found in a home (see Figure 37): resistive loads, inductive loads such as motors, and loads with solid state switching. Purely resistive loads, such as a lamp or an electric stove, do not create detectable amounts of electrical noise while in operation, although as a resistor, they can be expected to produce trace amounts of thermal noise (Johnson noise) at an undetectable level. In this particular case, only a transient noise is produced by minute arcing in the mechanical switch itself (wall switch) when the switch is turned on or off. A motor, such as in a fan or a blender, is modeled as both a resistive and inductive load. The continuous breaking and connecting by the motor brushes creates a voltage noise synchronous to the AC power of 60 Hz (and at 120 Hz). Solid state switching devices, such as MOSFETs found in computer power supplies or TRIACs in dimmer switches or microwave ovens, emit noise that is different between devices and is synchronous to an internal oscillator. Thus, the latter two classes contribute noise from both the external power switching mechanism (transient) and the noise generated by the internal switching mechanism (continuous).

In the United States, the Federal Communications Commission (FCC) sets guidelines on how much electrical noise AC-powered electronic devices can conduct back onto the power line (Part 15 section of the FCC regulations). Device-generated noise at frequencies between 150 kHz-30 MHz cannot exceed certain limits. Regulatory agencies in other countries set similar guidelines on electronic devices. Although this mainly applies to electronic devices, such as those that have solid state switching power supplies, this gives me some assurance about the type and amount of noise we might expect on the power line.

It is often extremely difficult to analytically predict the transient noise from the general description of a load and its switching mechanism because ordinary switches are usually not well characterized during their make-and-break times. However, it is possible to take a mapping approach by learning these observed signatures using supervised machine learning techniques. The challenge then becomes finding the important features of these transient pulses and determining how to detect the relevant ones of interest.

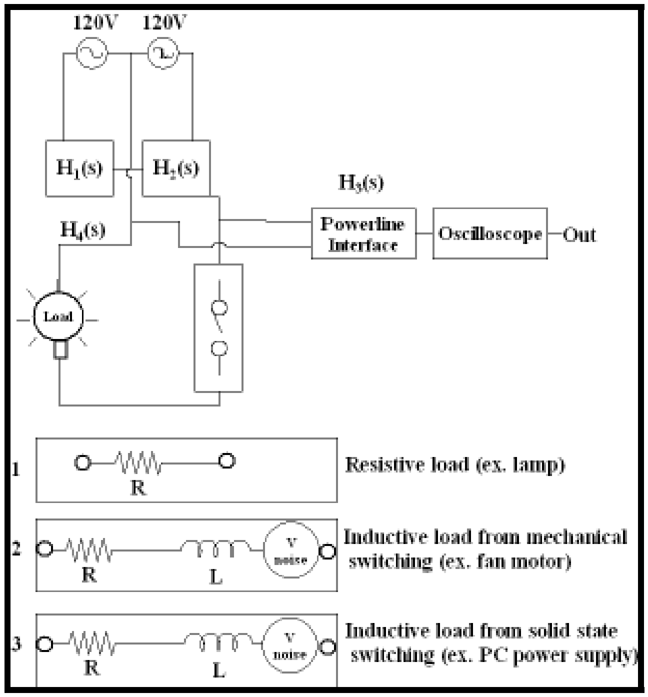


Figure 37: Overview of the powerline infrastructure and location of particular signal/noise transfer functions, $H_n(s)$. The bottom of the figure shows three general types of loads found in a home, a purely resistive, an inductive where voltage noise is generated from a continuous mechanical switching (motors), and an inductive load where voltage noise is generated by an internal oscillator of a solid state switch.

5.3.1.2 Hardware Details

To explore the idea of detecting and learning various electrical events in the home, I first built a custom data collector that consisted of a powerline interface with three outputs (see Figures Figure 38 and Figure 39). One output was the standard 60 Hz AC power signal, which I used during the initial testing and exploratory phase. The second output was an attenuated power line output that has been bandpass-filtered with a passband of 100 Hz to 100 kHz. The third output was similarly attenuated and was bandpass-filtered with a 50 kHz to 100 MHz passband. I chose these different filtered outputs to have the flexibility to experiment with different frequency ranges (see Figure 40). Both filtered outputs have a 60 Hz notch filter in front of their bandpass filters to remove the AC power frequency and enhance the dynamic range of the sampled data. I built the interface so that I could monitor the power line between hot and neutral, neutral and ground, or hot and ground. For the work reported here, I chose to observe the noise between hot and neutral (normal mode) because many loads that I would like to observe (such as table lamps and small appliances) do not have a ground connection.

I further chose to interface with only one 120V leg or branch of the electrical system. Most residential houses and apartments in North America and many parts of Asia have a single-phase or a split single-phase electrical system. This means there are two 120V electrical branches coming into the house to supply 240V appliances, but the two branches are still in phase. I found that the noises generated by devices of interest connected to the other electrical branch were already being coupled to the electrical branch I interfaced to, and so were detectable by the system. While this approach was practical and sufficient for the research prototype, we could also plug a coupler into a 240V outlet to ensure I have direct access to both electrical branches.

Finally, the outputs of the powerline interface are connected to a dual-input USB oscilloscope interface (EBest 2000) that has a built-in gain control. Each input has 10-bit resolution with a full scale voltage of 1V, so the least significant bit represents a voltage of 4 mV. The oscilloscope interface has a real-time sampling rate of 100 million samples/sec. A C++ API is provided, resulting in a simple software interface to the sampled signal.

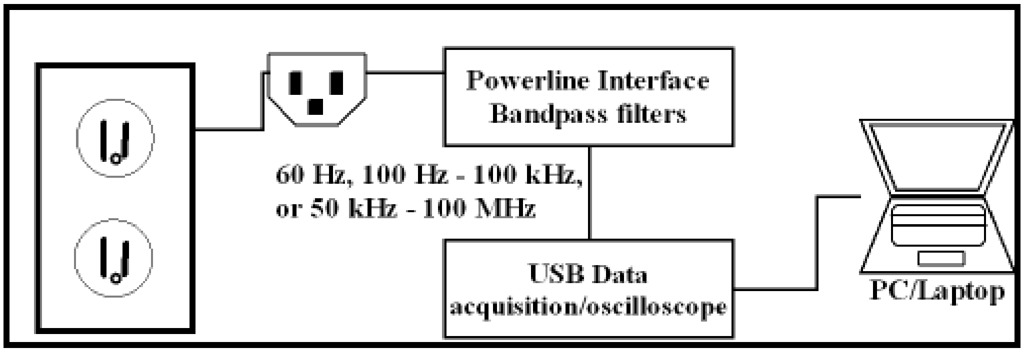


Figure 38: Block diagram of the powerline interface system.

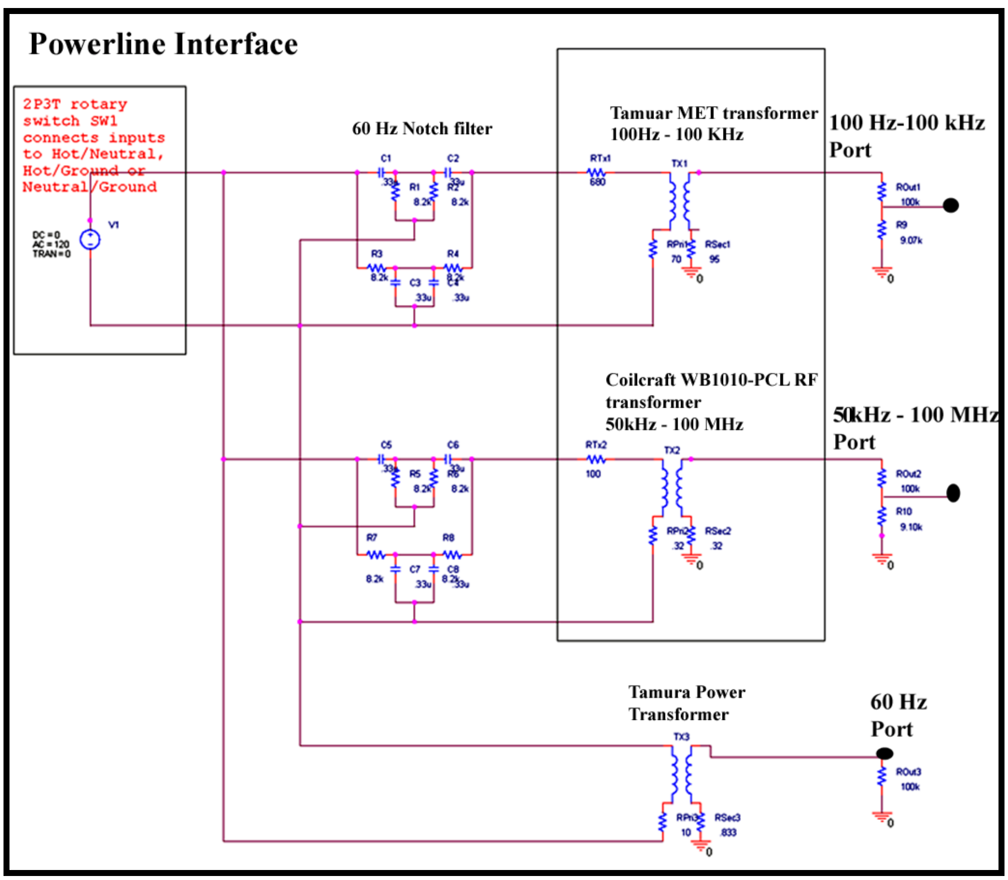


Figure 39: The schematic of the powerline interface device.

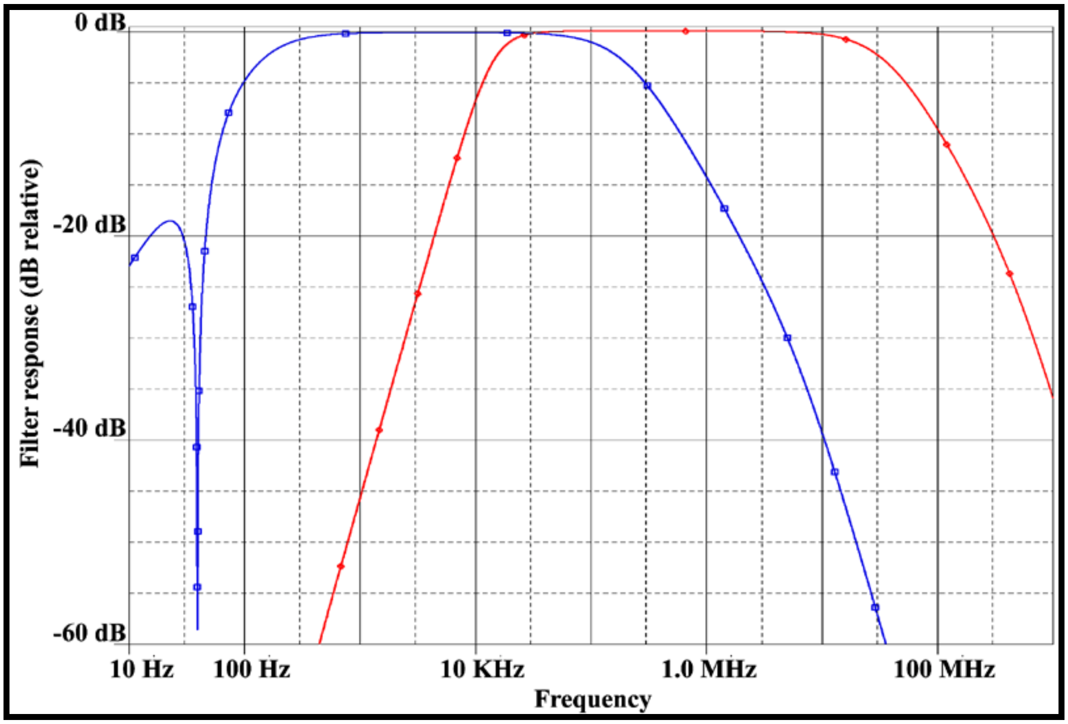


Figure 40: : A model of the frequency response curve of the powerline data collection apparatus at the 100 Hz – 100 kHz and the 50 kHz – 100 MHZ outputs. The 60 Hz dip is from the notch filter.

5.3.1.3 Software Details

For the software components of the prototype, I wrote a C++ application to sample the USB oscilloscope interface and perform a Fast Fourier Transform (FFT) on the incoming signal to separate the component frequencies for the analysis. The application also produces a waterfall plot, a commonly used frequency domain visualization in real-time used for visual inspection (such as in Figure 36). The application performs this analysis in nearly real-time, and it has the ability to record the data stream for post processing. A second application, written in Java, performs the machine learning and provides the user interface for the system. The Java application connects via a TCP connection to the FFT application and reads the data values. The Java application provides the user interface for surveying the home and remotely accessing the data from the powerline interface. I used the Weka [133] toolkit for the machine learning implementation.

5.3.1.3.1 *Detecting and Learning Transient Pulses*

The filtering hardware in the powerline interface removes most of the high frequency noise. Some broadband noise is always present, but typically at low amplitudes. To detect the transient pulses, I employ a simple sliding window algorithm to look for drastic changes in the input line noise (both beginning and end). These drastic changes, lasting only a few microseconds, are labeled as candidate signals and processed further. The sliding window acquires a 1-microsecond sample, which is averaged from the data acquired after performing the FFT on data from the data acquisition hardware. Each sample consists of frequency components and its associated amplitude values in vector form. Each vector consists of amplitude values for frequency intervals ranging between 0 and 50 kHz. I then compute the Euclidean distance between the previous vector and the current window's vector. When the distance first exceeds a predetermined threshold value, the start of the transient is marked. The window continues to slide until there is another drastic change in the Euclidean distance (the end of the transient). Although the threshold value was determined through experimentation, I can imagine learning and adapting the thresholds over time.

After having isolated the transient, we are left with N vectors of length L, where N is the pulse width in 1 microsecond increments and L is the number of frequency components (2048 in this case). A new vector of length L + 1 is then constructed by averaging the corresponding N values for each frequency components. The (L + 1)st value is simply N, the width of the transient. This value then serves as the feature vector for that particular transient.

For the learning algorithm, I employed a support vector machine (SVM) [81]. SVMs perform classification by constructing an N-dimensional hyperplane that optimally separates the data into multiple categories. The separation is chosen to have the largest distance from the hyperplane to the nearest positive and negative examples. Thus, the classification is appropriate for testing data that is near, but not identical, to the training data as is the case for the feature vectors for the transients. SVMs are appealing because the feature space is fairly large compared to the potential training set. Because SVMs employ overfitting protection, which does not necessarily depend on the number of features, they have the ability to better handle large feature spaces. The feature vectors are used as the support vectors in the SVM. I used the Weka Toolkit to construct an SVM, using labeled training data to later classify the query points.

5.3.1.4 Detectable Electrical Events

Having built the data collection apparatus, I first wanted to identify the variety of electrical devices I could detect with the apparatus and see which electrical devices would produce recognizable signatures that can be used for the machine learning software. For this exploration, I installed the apparatus in a single fixed location throughout the data collection process. I collected data with both the low frequency (100 Hz – 100 KHz) and high frequency (50 kHz – 100 MHz) ports. I took care to ensure no major electrical devices were activated (such as the HVAC, fridge, water pumps, *etc*.) by turning them off for the duration of the testing so I knew which devices were causing which response. For each electrical device of interest, I visually observed and collected noise signatures for turning the device on, turning it off, and its stable on state. Table 21 shows the various devices I was able to detect and the events I was able to observe for each device (on, off, continuously on state). Although I could have observed many more devices, I only show a representative sample of commonly used devices.

After initial experimentation, I found that most loads drawing less than 0.25 amps were practically undetectable Loads above that amount produced very prominent electrical noise (transient and/or continuous). This is related to the dynamic range of the data collection device—a collection device with more than 10 bits of resolution would be able to detect lower current devices. The devices listed in Table 21 showed not only strong but also consistently reproducible signatures. However, I did observe a limitation in how quickly I could switch a given device (*i.e.*, the delay between toggles). Depending on the device, I observed that approximately 500 ms delay between subsequent toggles was required for the data collection apparatus to detect a noise impulse successfully. This is largely attributed to the sampling and processing latency from the device (*e.g.,* USB latency plus processing delays on the PC).

While most devices produced a transient pulse only a few microseconds in duration in their energized state, certain devices continuously produced electrical noise while they were powered, as expected. For example, lamp dimmers or wall-mounted dimmer switches produced noise that was very rich in harmonics while they were activated. Similarly, microwave ovens also coupled broadband noise back on the power line during its use. These devices tended to produce strong continuous noise above 5 kHz and reaching up to 1 MHz. I also found that switching power supplies, such as from a laptop or PC, produced considerably higher noise in the 100 kHz – 1 MHz area than at the lower 100 Hz – 5 kHz range.

To understand devices that produced continuous noise, I tested various switching power supplies in isolation from other electrical line noise (see Figure 41). Using the higher 50 kHz – 100 MHz output on the data collection apparatus, I found that many of these devices produced more detectable continuous noise at the higher frequencies. At the lower 100 Hz – 5 kHz range, I saw fairly low amplitude, continuous noise, and a higher transient noise effect (from the flipping of the switch).

In the 100 Hz – 100 kHz range, motor-based devices, such as a ceiling or bathroom exhaust fan, exhibited slightly longer duration transient pluses when activated with a switch, but did not show continuous normal mode noise which would have been expected from the repeated electromechanical switching from the motor brushes. I attribute this difference to the 60 Hz notch filter, which blocked the 60 Hz power frequency. To confirm this hypothesis, I conducted another experiment in which I isolated various mechanically-switched devices (*e.g.*, fans) and looked at their noise output (see Figure 36). In the case of the fan, the data collection apparatus did indeed show the transient pulse, but not the continuous electrical noise.

From these observations, I was able to characterize the noise characteristics produced by different devices. I observed that transient noise produced from a single abrupt switching event (*e.g.*, a wall switch) tended to produce signals rich in high amplitude components in the lower frequency range (100 Hz – 5 KHz). Inductive loads featuring a solid state switching mechanism generally produced continuous noise in the 5 kHz – 1 MHz range. Inductive loads with mechanically switched voltages produce noise near 60 Hz, but the data collection apparatus filtered out much of that noise. I thus observed that the analysis of the frequency spectrum may be broken up into two parts. The lower frequency space (100 Hz – 5 kHz) is effective for analysis for transient noise events, such as those produced by wall switches. The higher frequency is better for continuous noise events, such as those produced by TRIACs and switching power supplies. I even observed that dim levels can also be gathered from the continuous noise frequency generated by the TRIACs. For this particular paper, I primarily focus on exploring transient noise events. Similar analysis and learning could be applied to continuous noise events.

Table 21: Electrical devices I tested and which events I was able detect. These devices also consistently produced detectable event signatures.

Device Class/Type	Devices Observed	On to Off Transition Noise?	Off to On Transition Noise?	Continuously On Noise?
Resistive	Incandescent lights via a wall switch	Y	Y	N
	Microwave door light	Y	Y	N
	Oven light/door	Y	Y	N
	Electric stove	Y	Y	N
	Refrigerator door	Y	Y	N
	Electric Oven	Y	Y	N
Inductive (Mechanically Switched)	Bathroom exhaust fan	Y	Y	N
	Ceiling fan	Y	Y	N
	Garage door opener	Y	Y	N
	Dryer	Y	Y	N
	Dishwasher	Y	Y	N
	Refrigerator compressor	Y	Y	N
	HVAC/Heat Pump	Y	Y	N
	Garbage disposal	Y	Y	N
Inductive (Solid State Switched)	Lights via a dimmer wall switch	Y	Y	Y
	Fluorescent lights via a wall switch	Y	Y	N
	Laptop power adapter	Y	N	N
	Microwave Oven	Y	Y	Y
	Television (CRT, plasma, or LCD)	Y	Y	N

Figure 41: The setup I constructed for isolating and testing the noise response for various electrical devices on an individual basis.

5.3.2 Feasibility and Performance Evaluation

To evaluate the feasibility and performance of the approach, I tested it in six different homes of varying styles, age, sizes, and locations. I first tested the transient isolation scheme in a single home. Next, I conducted a feasibility study in that home for a six-week period to determine the classification accuracy of various electrical events over an extended period of time. Finally, for the five other homes, I conducted a one-week study to reproduce the results from the first home.

5.3.2.1 <u>Transient Isolation Evaluation</u>

To evaluate the feasibility of the automatic transient detection scheme, I collected data from one home for a four-hour period and had the software continuously isolate transient signals. During that period, I actuated various electrical components and made a note of their timestamps. A total of 100 distinct events were generated during this period. For each event, I then determined if a transient was isolated successfully at the noted times. Table 22 shows the results of five different four-hour sessions. I report the percentage of successfully identified transients out of the number of event triggers. I believe the reason for the missed events was because of the static threshold algorithm. An adaptive threshold approach would mitigate this problem.

Table 22: Percentage of successfully identified transient pulses using the transient isolation scheme. Each test lasted for a four-hour period with approximately 100 possible transient events in each period.

Test 1 (% found)	Test 2 (% found)	Test 3 (% found)	Test 4 (% found)	Test 5 (% found)
98	93	91	88	96

5.3.2.2 Classifying Transient Events in Various Home

The aim of the extended 6-week evaluation was to determine the classification accuracy of various types of electrical devices and how often I had to retrain the system (signal stability over time). The other five deployments were used to show that I could detect events similar to those of the initial home and to show that the transient noise signatures were temporally stable in other homes as well. Despite the small number of homes, I tried to test a variety of homes and sizes, including older homes with and without recently updated electrical systems (see Table 23). I also included an apartment home in a six-story building, as I expected its electrical infrastructure to be somewhat different from that of a single family home. I was interested in testing the types of electrical devices listed in Table 21, so I ensured that the homes in which I deployed had most of these devices.

For the entire testing period, I installed the data collection apparatus in the same electrical outlet. For Home 1, I collected and labeled data at least three times per week during the 6-week period. The data collection process involved running the system and toggling various predetermined electrical devices (see Table 21 for examples). For each device toggled, I manually labeled each on-to-off and off-to-on event. In addition, I captured at least two instances of each event during each session. For Home 1, I selected 41 different devices for testing (82 distinct events) and collected approximately 500 instances during each week. Thus, approximately 3000 labeled samples were collected during the 6-week period.

I collected and labeled data in a similar manner for the shorter 1-week deployments. I collected training data at the beginning of the week and collected additional test data at the end of the week. At least 4 instances of each event were gathered for the training set. Because I had control over the events, the number of distinct events were fairly equally distributed among the data and not biased towards a single device or switch for all the 6 homes.

Table 24 and Table 25 show classification accuracies for the different homes I tested. For Home 1, I show the classification accuracy of test data gathered at various times during the six weeks using the training set gathered during the first week. The average overall classification accuracy in Home 1 was approximately 85% (Table 24). I also show the accuracy of the classification for varying training set sizes. Because there can potentially be many events of interest in the home, making the training process an arduous task, I wanted to find the minimum number of samples that would provide reasonable performance. The results suggest that there is only a slight decrease in classification over the 6 week period. The results also suggest that a small number of training instances result in lower classification accuracies. In addition, the majority classifier had accuracies of only about 4% on average, because of the equal distribution of the distinct events in the training and test data,

As reported, increasing the number of training instances did increase the classification accuracy. A small number of training samples makes it very important to have accurate training data. Mislabeling of a single training sample can have major impacts on the learned model. I even caught ourselves accidentally mislabeling a few events. For example, the on and off event labels I noted were sometimes flipped for a particular electrical device. Thus, this highlights the importance of designing a training or calibration scheme that mitigates human error during the training and labeling process.

The results from the one-week deployments in the five other homes are shown in Table 25, and the test data from the end of the week showed promising results. I did not see any significant differences in accuracy between old and new homes. The lower classification accuracy for Home 5 was the result of a low frequency noise that interfered with the transient events. Although I could not find the origin of that noise, I can imagine building a smarter system that learns these erroneous noise events to avoid incorrect classifications.

Table 23: Descriptions of the homes in which the system was deployed. Home 1 is where I conducted the long-term 6-week deployment.

Home	Year Built	Electrical Remodel Year	Floors/ Total Size (Sq Ft)/ (Sq M)	Style	Bedrooms/ Bathrooms/ Total Rms.	Deply. Time (weeks)
1	2003	2003	3/4000/371	1 Family House	4/4/13	6
2	2001	2001	3/5000/464	1 Family House	5/5/17	1
3	1999	1999	1/700/58	1 Bed Apt	1/1/4	1
4	2002	2002	3/2600/241	1 Family House	3/3/12	1
5	1935	1991	1/1100/102	1 Family House	2/1/7	1
6	1967	1981	1/1500/140	1 Family House	2/1/7	1

Table 24: Performance results of Home 1. The accuracies are reported based on the percentage of correctly identified events. Training happened during Week 1, and I reported the accuracies of the classifier for test data from subsequent weeks using that initial training set from week 1. Overall classification accuracy of a simple majority classifier was 4%.

	SVM accuracies during specific weeks of testing					
Training Set Size/Instances per event	Week 1 (%)	Week 2 (%)	Week 3 (%)	Week 4 (%)	Week 5 (%)	Week 6 (%)
164/2	83	82	81	79	80	79
246/3	86	84	85	84	82	83
328/4	88	91	87	85	86	86
410/5	90	92	91	87	86	87

Table 25: Performance results of various homes. The accuracies are reported based on the percentage of correctly identified toggled light switches or other events in the test data set. The results of a majority classifier are also shown. For each home, the training of the data occurred at the beginning of the week and the test data set was gathered at the end of that week.

Home	Distinct events	Training set (events)	Test set (events)	Accuracy (%)	Majority classif. (%)
2	82	328	100	87	4
3	48	192	96	88	6
4	76	304	103	92	3
5	64	256	94	84	3
6	38	152	80	90	8

5.3.3 Discussion of Limitations and Future Improvements

Although I found promising results with the system, it is not without some limitations and some future considerations. In the current implementation, I purposely analyzed the lower frequency spectrum where solid-state switching devices would produce the lowest interference from potential continuous noise. However, at the same time, this choice limits the feature space. Looking at a larger frequency spectrum could provide better classification for certain transient events. In addition, a fully functional system must be able to detect and to adapt to random noise events when looking for transient pulses. In the future, I plan to improve the feature extraction step. I focused on only the amplitudes of the component frequencies. Phase difference between component frequencies, however, should be considered as part of a feature extraction scheme. In addition, the exploration of other machine learning techniques and application of more domain knowledge of the transient signals may also prove valuable in building a better classifier.

Another consideration is the scaling of the approach. Although unlikely in domestic settings, compound events, such as two lights flipped simultaneously, can produce errors in classification because their combined transient noises produce different feature vectors. This type of event is more of a concern in an extremely large home with many residents or in an apartment building that does not have individually metered units. If users regularly flip light switches nearly simultaneously, this could be trained as a separate event from the individual switches.

I have been primarily focused on domestic environments, but this type of system can also be applied to commercial settings. However, compound events and electrical noise in these settings may become a more significant issue. Another issue is that the electrical lines may be so long that the noise does not reach the analyzer. Commercial buildings typically have multiple electrical legs, and to mitigate problems with compound events and line distance, I could install multiple line noise analyzers throughout an office building to isolate the analysis to certain sections of the building. The approach will have some difficulty differentiating between individual events among a dense collection of proximal devices that have similar switching and load characteristics. For the approach to scale to these environments, the entire frequency band may needs to be considered. Another drawback of commercial buildings is that they tend to have more noisy components, such as large HVAC systems, connected to the power line that can produce many other transients and mask the pulses of interest..

The system is more appropriate for detecting and learning fixed electrical devices than mobile devices or portable devices. Though I could support them, portable devices require training the system on any possible outlet that they may be plugged into. In addition, plugging the device into an extension cord or power strip might produce a different fingerprint than plugging it into an electrical outlet directly. With a well-defined set of events that should be detected, a suitable training plan can be devised, but it may become time-consuming as the set grows larger.

In some respects, this system represents a tradeoff between the two categories of systems I mentioned above. Unlike the first category of prior work, the system does not require the deployment of a large number of sensing units throughout the home. A single data collection module is certainly easier to physically deploy and maintain than a large array of distributed sensors, though one could argue that a single point of failure has been introduced (*e.g.*, what if someone accidentally unplugs the data collection module?). On the other hand, this simplicity of physical installation and maintenance has its cost in terms of training the machine learning algorithm to recognize a significant number of electrical loads. The appropriateness of this tradeoff is thus expected to be application dependent.

5.4 Airbus: Leveraging Existing HVAC Systems

The development of low-cost and easy-to-deploy sensing systems to support activity detection in the home has been an important trend in the pervasive computing community. Much of this research has centered on the deployment of a network of inexpensive sensors throughout the home, such as motion detectors or simple contact switches. Although these solutions are cost-effective on an individual sensor basis, they are not without some important drawbacks that limit their desirability as research tools as well as their likelihood of eventual commercial success through broad consumer acceptance.

I have developed an approach that provides a whole-house solution for detecting gross movement and room transitions by sensing differential air pressure at a single point in the home. The solution leverages the central heating, ventilation, and air conditioning (HVAC) systems found in many homes. The home forms a closed circuit for air circulation, where the HVAC system provides a centralized airflow source and therefore a convenient single monitoring point for the whole airflow circuit.

Disruptions in home airflow caused by human movement through the house, especially those caused by the blockage of doorways and thresholds, results in static pressure changes in the HVAC air handler unit when the HVAC is operating. The system detects and records this pressure variation from differential sensors mounted on the air filter and classifies where exactly certain movement events are occurring in the house, such as an adult walking through a particular doorway or the opening and closing of a door. Preliminary results show I can classify unique transition events with up to 75-80% accuracy. I also show how to detect movement events when the HVAC is not operating.

The principal advantage of this approach, when compared to installing motion sensors throughout an entire house space, is that it requires the installation of only a single sensing unit (*i.e.*, an instrumented air filter) that connects to a computer. By observing the opening and closing of doors and the movement of people transitioning from room to room, the location and activity of people in the space can later be inferred. In addition, detecting a series of room transitions can be used for simple occupancy detection or to estimate a person's path in the house.

Because of the use of a single monitoring point on an existing home infrastructure (the HVAC air handler, in this example) to detect human activity throughout an entire house, I consider this system a member of an important new class of activity monitoring systems that I call infrastructure mediated sensing.

5.4.1 Deployability: Prevalence of Central HVAC Systems

Although central home HVAC systems are not as prevalent in some geographic regions as plumbing or electrical infrastructure, the approach is still useful in the significant number of homes or buildings that do have central HVAC. Because central HVACs are more efficient than using a collection of window units [84], the upward trend in energy cost has driven the use of central HVAC systems to a growing number of homes. In 1997, 66% of the homes in the United States and Canada were reported to have central HVAC, and its prevalence is growing at a fast rate [9, 79, 119]. In addition, nearly all new homes built in the southern part of the U.S. and 80% in the rest of the U.S. and Canada have central HVAC installed during construction [79]. Europe and Australia show a similar trend, with approximately 55% homes using central HVAC [53, 74]. However, in some Asian counties such as Japan and Korea, central HVAC is not as common in homes because of the smaller dwelling sizes prevalent in those regions. If the home is very small, such as a small Japanese or Korean home, the deployment of distributed direct sensors may not be as arduous because of the smaller amount of floor space to cover. Regardless of the regional prevalence of central HVAC, the value of the approach becomes more apparent in larger homes or in assisted living facilities that have many rooms, precisely the settings where installing many distributed sensors is economically unattractive.

HVAC systems will probably increase in prevalence because they can provide more functionality than just heating and cooling. Recent EnergyStar reports have shown that running the HVAC for longer periods of time, but using alternate conditioning features, such an air-to-air exchanger, is more energy efficient [84]. This EnergyStar report also recommends that HVAC units incorporate whole house HEPA filtration. Construction codes, such as for hospitals and assistive care facilities, also have a minimum air movement requirements to ensure proper filtration [6, 88]. All of these factors increase the motivation for having the HVAC in operation, increasing the effectiveness of the sensing approach. If we take a standard 2-ton (24,000 BTU) HVAC unit and run the air handler's fan continuously for an entire month it would cost about $6 US (assuming an electricity price of $0.05 US per 1 kW-h), which would need to be balanced against any value-added capability the sensing provides.

5.4.2 Approach and System Details

I instrumented an HVAC's air filter with five pressure sensor units, each sensing in both directions (see Figure 46). The sensors do not interfere with the operation of the air filter or HVAC and instrumenting the air filter allows for easy installation in standard HVAC units. The sensors on the air filter capture the pressure differential across the filter in the air handler chamber. The magnitude of the pressure change across all the sensors is used to identify unique disruptions in airflow in the physical space. Machine learning techniques then classify these disruption signatures.

5.4.2.1 Theory of Operation

The HVAC system's air handler is a device used to circulate conditioned air throughout a space. Typically, an air handler is a large, sealed metal box containing a blower, heating/cooling coils, filter, and dampers (see Figure 42). An air handler consists of a discharge, or supply, chamber where the conditioned air exits through ductwork, and is drawn back into the return chamber through a separate set of vents and ductwork. During its operation, a pressure differential, ΔP, is built up in the blower chamber, know as the total static pressure. The static pressure is a measure of resistance imposed on the HVAC's blower in the air handler. The static pressure is affected by a variety of factors that impede the airflow between the supply and return. These includes the length of ducting, number of fittings used in the ductwork, closed air vents, or dirty air filters. When installing an HVAC unit, a technician usually takes care in properly balancing the static pressure to ensure its proper operation. This includes installing sufficient supply and return ductwork in the right locations. Technicians also install ductwork to various rooms to ensure effective coverage. Figure 42 shows a cross-sectional drawing of a home and example locations of the supply and return vents and the potential airflow paths.

When the HVAC is running, air flows from the supply vents to the return vents through the conditioned space (*i.e.*, a room). There is always some airflow from each supply vent to all the return vents. Depending on the location of the vents, the airflow paths and amount of airflow can vary. When there is disruption to the airflow, there is a change in the static pressure in the air handler as a result of the resistance in the airflow. Depending on the location of return vents, a disruption in airflow can cause a more persistent change in the overall static pressure, such as from a direct blockage of a return vent. In a home, one contributor to this airflow disruption is doorways, where airflow can either be disrupted by the closing or opening of a door or the partial blockage of an adult passing through the threshold. Sometimes, an individual may even feel the "resistance" from the airflow when trying to open a door. Also depending on the location in the house where this disruption is occurring, the “resistance” differs because of the airflow path. Another way to look this phenomenon is using an electrical circuit analogy (Figure 43).

When the HVAC is not in operation, the ductwork acts as a “wave guide.” Significant airflow produced in the space flows through the ductwork. Although small movements cannot generate enough airflow, the movements of large surfaces, such as doors, can produce detectible amounts of airflow through the air handler. Thus, there are opportunities to detect certain movement in the space with the HVAC both in operation and not in operation.

I use the air filter chamber as the sensing point for two important reasons. First, it is between the supply and return chambers and near the blower assembly, making it a good place for recording the static pressure changes. Second, the filtration unit typically has the easiest access to the air handler, potentially making it easy-to-deploy for installers and end-users. The static air pressure is determined by installing pressure sensors facing each direction on the air filter and calculating the differential (ΔP). A single differential pressure sensor would also be appropriate. However, using two pressure sensors makes their placement easier. This is because typical differential pressure sensors have the pressure ports on one side, which requires routing an air tube to the other side. The sensors required for the approach are capable of measuring up to 2 bars of pressure and sensitive enough to measure small pressure changes down to .1 mbar. Figure 44 shows a graph of the change in static pressure as a door it is opened and closed. There is an initial spike in the pressure followed by a flattening. After the door is reopened, the pressure returns to the previous state.

I placed multiple pressure sensors on the air filter to help estimate the location of the resulting pressure change. In standard ductwork, multiple ducts combine to feed larger trunks, which then attach to the supply and return chambers. Because multiple ducts feed into the chambers, pressure sensors closer to the ductwork that is contributing to the airflow disruptions will see greater initial change in pressure compared to the other sensors.

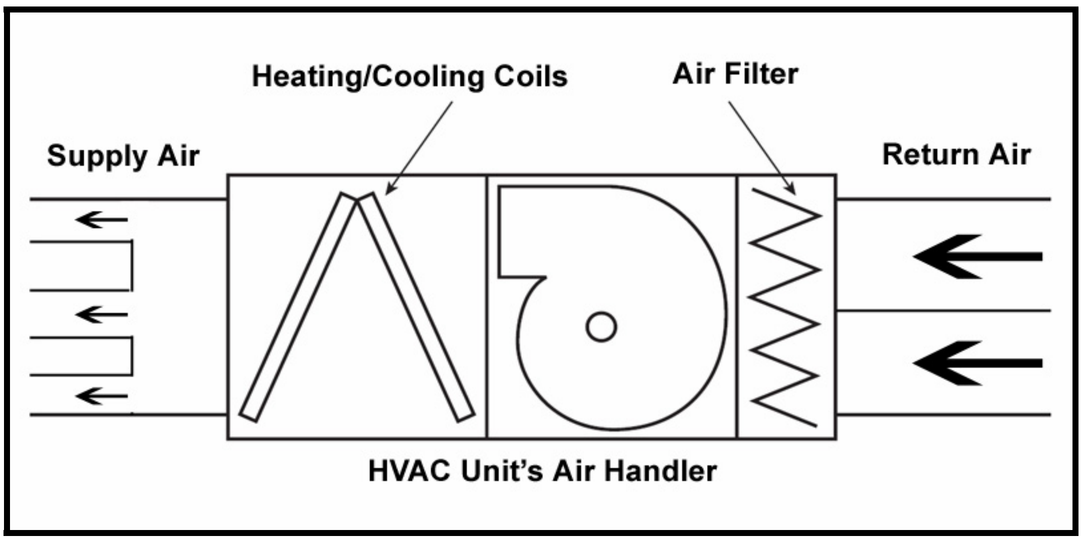


Figure 42: Cross section of a HVAC air handler unit.

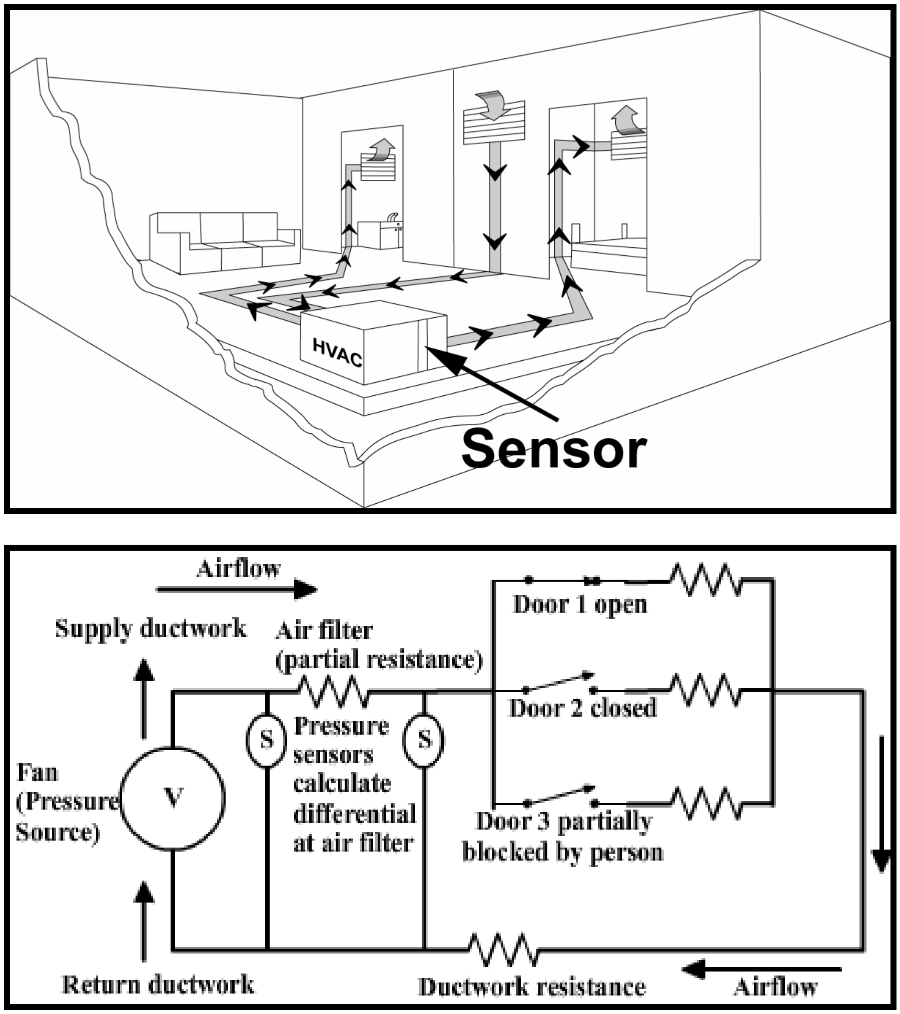


Figure 43: Diagram of airflow from return and supply ducting in a home (top). Electrical circuit diagram analogy of the sensing approach (bottom).

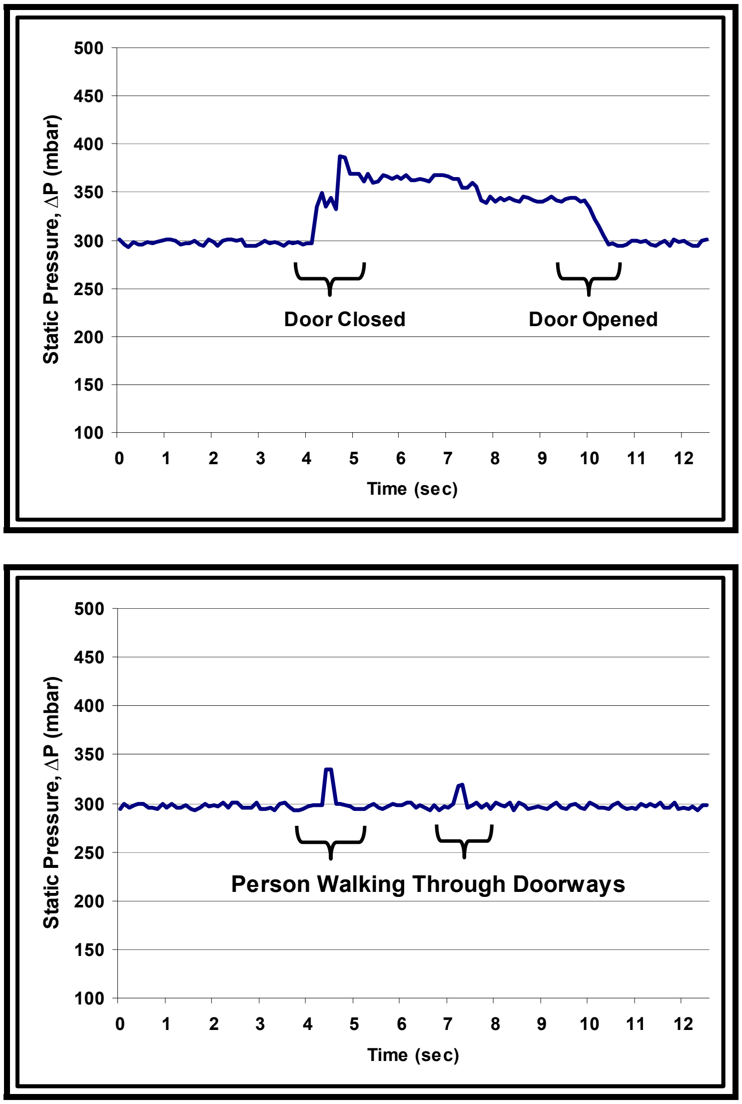


Figure 44: Examples of the pressure changes in the air handler as a result of an opening and closing of a door (left) and an adult walking through two different doorways (right).

5.4.2.2 Data Collection Hardware and Software

I used the Intersema MS5536 piezoresistive pressure sensor module for building the sensor units. The MS5536 modules are high resolution (.1 mbar), provide a stable output of up to 2 bars, and have a maximum rating of up to 5 bars, which is sufficient for many residential HVAC applications. The modules incorporate a temperature sensor for proper pressure compensation, a built-in 15-bit ADC, and also provide easy communication using SPI. To obtain pressure differentials, the MS5536 uses two sensors facing opposite directions. The pressure sensor modules are connected to an ATMEL microcontroller (see Figure 45). The microcontroller samples the pressure and temperature sensors on the MS5536 and calculates a temperature-compensated pressure value every 35 milliseconds. Intersema's temperature compensation formula was used in the calculations [55]. The pressure values are then transferred to a PC via a USB connection. Multiple sensor units are connected to a single PC using a USB hub. I chose to use individual units to give me some flexibility when experimenting with a variety of sensor placements on the air filter. The sensor units are small enough to attach easily to the air filter with zip ties. In a production version, the sensors would be mounted on a framed bracket that would just attach to the air filter. A fully deployable unit would have all the pressure sensors feeding into it a single microcontroller. A unit incorporating five differential pressure sensors costs about $100 USD at low volumes.

The software used in the data collection is written in C++ and records the temperature-compensated pressure data, the raw pressure values, and the temperature from the sensors units. The application continually timestamps and records the pressure-related data from all the sensor units every 50 millisecond.

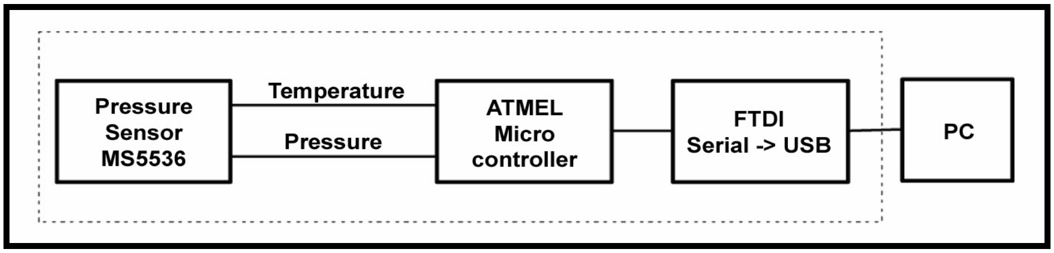


Figure 45: Block diagram of the pressure sensor unit.

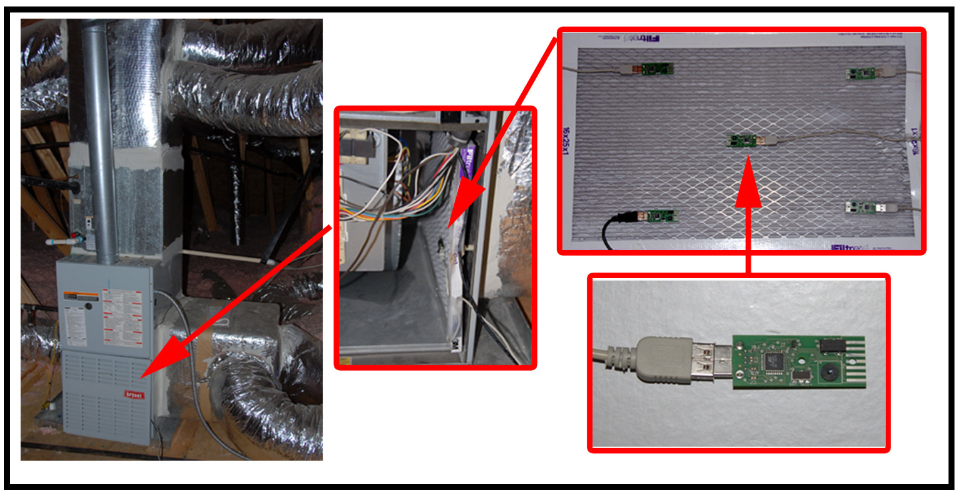


Figure 46: I instrument a standard HVAC air filter with pressure sensors that are able to detect airflow in both directions. The air filter is then installed in the HVAC's air handler unit.

5.4.2.2.1 *Detecting Door Opening and Closing Events*

I observed two important features that were characteristic of door opening and closing events. When a door is closed, there is first an initial abrupt change in static pressure (change in ΔP) followed by persistent change until the door is reopened (see Figure 44). After opening the door, the static pressure gradually drops to the previous state. I detect this phenomenon by first looking for a significant change in the static pressure by at least one of the five sensing units. I do this by comparing the average of the 5 previous pressure differential reading with the current. When there is a pressure change greater than 10 mbar, I record the subsequent pressure values for further processing until there are no more changes for a period of 4000 ms. All other sensors also record at the same time. The 10 mbar threshold is to avoid detecting any slight variations from the senor or noise from the ADC. From the recorded data I next extract the initial pressure value, the initial maximum pressure change, and the resulting final stable pressure. These features are extracted for all 5 sensor units, producing a final feature vector of 15 components.

5.4.2.2.2 *Detecting Movement of People through Doorways*

A person passing through a doorway is a brief event, and the size of the individual can vary, decreasing the likelihood of detection. However, I still wanted to explore the feasibility of detecting those events. During the experimentation, I observed variations in the static pressure as individuals moved through various doorways. Unlike the door events, the changes in pressure are very short-lived. There is a slight change in the static pressure and then the pressure settles back to its original state. The effect is dependent on the location of the supply and return vents relative to the doorway and the ratio of the size of the person to the size of the doorway. From the observations, a ratio of 1:3 resulted in detectable airflow disruptions (>10 mbar).

I isolated these events by comparing the average of the 5 prior pressure differentials to the current. I recorded the pressure values when there was a change of more than 10 mbar by at least one sensor unit. All other sensor units also triggered to record at the same time. Values were gathered until the pressure stabilized. I use the maximum pressure change from each of the 5 sensor units as the feature vector.

5.4.2.2.3 *Detecting Movement of People through Doorways*

When the HVAC is not operating, there is no static pressure build-up in the air handler. Instead, the pressure is equal to the atmospheric pressure of approximately 1 bar. Any significant airflow generated in the conditioned space is guided through either the supply or return ducts and eventually reaches the sensor units on the filters. The sensitivity of the sensor units make it possible to detect airflow reaching the sensors. I can use the pressure values from both sides of the filter to help determine where the airflow originated. Similar to the previous approaches, I also use the multiple sensing points to help localize the origination of the induced airflow. Theoretically, it is also possible to detect airflow caused by people moving near an air vent and by other devices, such as a ceiling or desk fan. However, these events produce very small amounts of airflow and require more expensive, high-resolution and low-noise pressure sensors. In this case, I focus on just the movement of doors when the HVAC is not operating.

When the HVAC is off, I isolate door events by comparing the average of the 5 prior pressure differentials to the current. I then record the pressure values when there are any changes of more than 10 mbar by at least one sensor unit. All other sensor units are recorded at the same time. Values are gathered until the pressure stabilizes, and the feature vector of the maximum pressure change from each of the 5 sensor units is calculated.

5.4.2.2.4 *Classifying Events*

For the classification scheme, I used support vector machines (SVMs). SVMs perform classification by constructing an N-dimensional hyperplane that optimally separates the data into multiple categories. The separation is chosen to have the largest distance from the hyperplane to the nearest positive and negative examples. Thus, the classification is appropriate for testing data that is near, but not identical, to the training data as is the case for the feature vectors in the approach. In addition, SVMs can automatically determine the appropriate kernel type based on the data build characteristics, so kernels beyond linear functions can be factored in. For the experiments, I created three different SVM models for each of the three scenarios, using their respective feature vectors with each transition event labeled as the class. The open transition and the close transition for each door of interest were used as the classes in the learner. This was the case for both the HVAC in operation and not in operation. In the case of classifying human movement through a doorway, I do not differentiate between the directions of movement, thus the class labels were of the door where the movement occurred.

5.4.3 Performance Experiment and Results

The goal of the feasibility experiments was to determine if and how often I could detect transition movements (*e.g.,* adults walking through doorways and the opening and closing of doors) and how accurately the system could classify unique transition events. I report the results from experiments in four different homes for the following three conditions: opening and closing of doors while the HVAC is in operation, adults moving through doorways while the HVAC is in operation, and the opening and closing of doors while the HVAC is not in operation.

5.4.3.1 Setup of Experiments

I conducted experiments and observations in four different homes for a period ranging from 3 to 4 weeks (see Table 26). Home 1 and Home 2 were fairly large homes, with Home 1 having three separate central HVAC units, and Home 2 having two separate central HVAC units. I instrumented all three units in Home 1 and one unit in Home 2. Homes 3 and 4 were smaller apartments with a single, central HVAC system. Thus, I evaluated a total of six different spaces and HVAC units. For each HVAC unit, I installed an instrumented air filter (see Figure 46). The sensors were securely attached to prevent any movement from the airflow. The cables were run around the edge of the filter to prevent them from being drawn in to the fan assembly. Finally, the cables were connected to a laptop placed near the HVAC unit.

I used two techniques for obtaining labeled ground truth data. First, throughout the 3-4 week period I manually labeled numerous door close and open events and a person walking through doorways with the house in a closed and sealed state (windows and exterior doors closed). Second, I captured data for a longer time period using motion sensors placed at various locations in the house. Sensors on both sides of the top of the doorways (facing downwards) detected the direction of movement through the doorway. Although I was not able to accurately differentiate door movement and people movement, the motion sensors did allow me to determine if any transition events occurred at various times during the day. The large dataset allowed me to partition the data into sufficient training and test sets.

Table 26: Descriptions of the homes in which the system was tested. The deployment lasted approximately 3-4 weeks.

Home	Year Built	No. of HVAC Units Tested	Floors/ Total Size (Sq Ft)/ (Sq M)	Style/ No. of occupants	Bedrooms/ Bathrooms/ Total Rms./ Doorways considered	Deploy Length (weeks)
1	2003	3	3/4000/371	1 Family Home/3	4/4/13/20	4
2	2001	1	1/1600/149	1 Family Home/5	3/2/7/10	3
3	1997	1	1/700/58	1 Bed Apt/2	1/1/5/5	3
4	1986	1	1/500/46	1 Bed Studio/1	1/1/3/4	4

5.4.3.2 Manually-labeled Controlled Experiments

In these experiments, I wanted to test the feasibility of accurately classifying the various kinds of unique door or movement events in a quasi-controlled manner. For all four homes, I manually labeled sensor readings for each event using a remote handheld computer wirelessly connected to the data collection PC. I was able to accurately label the sensor readings for each of the five sensors after triggering the various events. I then used the feature extraction algorithms to construct the appropriate feature vectors to feed the classifier. For these experiments, all interior doors of interest were kept in the open position (90 degrees from the opening), while I was manually opening and closing each door. For the human movement experiments, the same individual triggered those events. I collected 25 instances for each of the doorway events three different times during the 3-4 week period (175 instances).

Table 27 shows the classification accuracies of all the spaces. I have also included an example confusion matrix (Table 28). It is clear that door transition events were more accurate than people transitions. However, the overall accuracy of classifying unique movement events was around 65%, which is still promising. Door events were classified correctly on an average of 75-80% of the time, suggesting that I can combine both of these events to provide good predictions on the location or movement of people through the space. Some of the low classification accuracies, such as from Floor 2 in Home 1, were attributed to the lack of door and doorways. That space was very open with the air vent a significant distance away from the interior doors. The results of the HVAC off experiment also showed some promising results (see Table 31). Although the accuracies are lower than with the HVAC in operation, there is still some predictive power. The higher performance came in smaller spaces where the vents tended to be closer to the doorway and in spaces where there were many vents, such as Homes 1 and 2.

5.4.3.3 <u>Long-term Deployment</u>

The results show that a larger percentage of events were detected with the HVAC in operation than with it in the off state. The reason for the lower percentage for the HVAC off case was because of the location of the return and supply vents. In some cases, the vents were not close enough to a door for the airflow to reach the sensing units, which I saw in the controlled experiment. The smaller spaces and the spaces with many doorways actually resulted in a higher number of detectable events. This is attributed to the greater number of vents and the likelihood that the doorways were near vents. The results with the HVAC in operation are promising, with almost 80% of the events being detected when compared to the motion sensors. Table 30 shows the results of classifying unique events in the house. I applied the SVM classification scheme to the entire in situ dataset for each of the 4 homes (6 spaces). This dataset included events from all three of the possible conditions (door open/close with HVAC on and off and human movement with HVAC on). The triggering of the motion sensor was used to provide the location label to the air pressure data collected by the sensing system. Because I did not know the type of event, I used the signal response to determine the event (*i.e.*, person or door).

I report the accuracy of the approach using 10-fold cross validation across the entire data set. Compared to the first controlled experiments, the overall accuracy on average is 15-20% lower. However, considering that I did not control the various other events occurring during that time, the results are still promising with classification accuracies between 60-70%. From these I can see that the status of other doors did not have a large impact on the classification accuracy of detecting door transitions with the HVAC off. The larger difference while the HVAC is in operation compared to the controlled experiment does indicate the door states have an impact on the pressure differentials, as expected. However, since I trained from a subset of the entire dataset, the learner seemed to incorporate the various door combinations. This is intuitive because people tend to be consistent with how they leave many of their doors throughout the day, while only actually using a few doors.

Table 27: Performance results of the manually-labeled experiments with the HVAC in operation. The accuracies are shown using 10-fold cross validation.

Home/ Floor	No. of Doorways Tested	No. of Door Instances/People Instances	Door Majority Classif. (%)	Door Classif. Accuracy (%)	People Majority Classif. (%)	People Classif. Accuracy (%)
1/1	5	375/375	21	84	23	72
1/2	4	300/300	18	61	18	42
1/3	11	825/600	9	77	12	61
2	10	750/400	8	73	10	63
3	5	375/375	20	74	20	70
4	4	300/300	26	81	25	76

Table 28: Confusion matrix of the classification results from the controlled experiments in Home 1/3 (HVAC in operation). D1 - D11 represent each doorway.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
D1	72	0	0	0	1	0	0	1	0	0	1
D2	1	57	0	2	0	2	6	4	0	1	2
D3	0	1	60	1	0	1	3	2	5	2	0
D4	0	0	1	57	2	0	0	4	3	6	2
D5	4	0	1	4	52	5	0	6	2	0	1
D6	5	1	0	0	6	53	4	2	0	1	3
D7	0	2	3	3	0	1	61	0	3	2	0
D8	6	0	0	0	2	1	1	55	5	0	5
D9	1	0	4	0	1	5	2	0	59	2	1
D10	2	2	7	0	3	3	8	0	2	43	5
D11	0	1	0	0	0	2	0	0	0	2	70

Table 29: Performance results of the manually labeled door open/close events for when the HVAC is not in operation.

Home/ Floor	No. of Doorways Tested	No. of Door Event Instances	Door Majority Classif. (%)	Door Classif. Accuracy (%)
1/1	5	125	20	66
1/2	4	100	25	47
1/3	11	275	9	64
2	10	250	10	69
3	5	125	20	71
4	4	100	25	68

Table 30: The percentage of events that the approach was able to detect. This is determined by comparing the number of detected events to the number of doorway events gathered by the motion sensors. These results include events detected with HVAC both on and off.

Home/ Floor	No. of Doorways Tested	No. of Total Motion Sensor Events	No. of Total Detected Events	HVAC On: Detected Events (%)	HVAC Off: Detected Events (%)
1/1	5	53	48	91	68
1/2	4	94	60	64	35
1/3	11	238	195	82	73
2	10	467	334	72	64
3	5	245	198	81	70
4	4	61	51	84	77

Table 31: The performance of using the learning approach to the data from the long-term deployment. The motion sensor data was used to label each event, so the dataset consists of in situ event instances. The accuracies are show using 10-fold cross validation.

Home/ Floor	No. of Doorways Tested	No. of Doorway Transition Instances	Door Majority Classif. (%)	Door Classif. Accuracy (%)	People Majority Classif. (%)	People Classif. Accuracy (%)
1/1	5	48	26	65	28	61
1/2	4	60	26	53	26	42
1/3	11	195	14	72	17	63
2	10	334	19	62	12	65
3	5	198	28	72	23	71
4	4	51	34	78	38	81

5.4.4 Discussion

This approach is certainly not without limitation. It does require a training phase and further research is still needed to come up with a mechanism to ease the training process. Some possible directions are to use events generated from other calibrated systems (water line or power line) to feed the training of this system. Although this might not cover all possible training cases, it can be used to relieve some of the burden. Those systems can also provide continual feedback for verifying the training set. In addition, partial training may also be feasible for certain applications, where only certain doorways are first trained. Then, if there is any interest in observing other events, the training can occur after the fact and the other past events can be reviewed.

I considered only the amplitude of the static pressure change and using multiple pressure sensor units to determine unique movement and door events. Other possible approaches would look at the changes in the laminar airflow. Although I use the temperature values for calculating the temperature-compensated pressure values, I could use the temperature reading as an additional feature. The current focus was on residential central HVAC systems, but the system can scale reasonably to larger units used in most commercial buildings. Further investigations are needed to explore those systems. The feasibility experiments did not directly factor in the opening and closing windows and doors. Finally, the current approach does not directly address compound events—multiple simultaneous door and person movements— although these events occurred in the long-term studies. Modeling airflow variations and creating a new learning approach that incorporates that domain knowledge could address this.

The combination of different types of infrastructure mediated sensors offers a number of attractive properties for deployment of useful applications in the home. For example, the combination of detecting human-initiated electrical [101] or water events [36] with the work on movement detection through airflow sensing enables a variety of new approaches for integrating energy and environmental conservation with ordinary human activities in the home. A system could alert an individual that he or she should attend to an energy or environmental conservation task, such as turning off an unneeded light or a running faucet, when the system detects that he or she is near that part of the house. The combination of electrical event detection and airflow detected movement information can also provide important correlation data for energy conservation applications by relating a person's usage of the physical space with the usage of electrical devices. One could design an energy-efficient, zoned HVAC unit that selectively heats or cools each zone on the basis of activity information passively sensed through the HVAC system itself, which would offer a tremendous installation and maintenance cost benefit over competing distributed sensing approaches.

CHAPTER 6

CONCLUSION AND FUTURE DIRECTIONS

In this dissertation, I first discussed the development and evaluation of two technologies, PowerLine Positioning and BlueTrack. PowerLine Positioning is an indoor localization system that supports the absolute tracking of people and objects in a home, and BlueTrack provides the tracking of relative proximity between people and objects in any space. PowerLine Positioning is an inexpensive system that uses the powerline infrastructure in a home. It requires only the addition of two plug-in modules to track simple location tags down to one meter. BlueTrack is a Bluetooth-based proximity tracking system that can determine three levels of proximity between custom Bluetooth tags and Bluetooth-enabled devices passively and without the need for active pairing between devices. Finally, I presented an important new class of activity monitoring systems that I call ***infrastructure mediated sensing (IMS)***, which incorporates minimal monitoring or probing points on an existing home infrastructure (electrical, plumbing, HVAC, *etc.*) to detect human activity throughout an entire house.

I conducted technical evaluations of these IMS-based solutions. I gathered various performance measures of PowerLine Positioning from a number of in-home installations to gather its operational parameters. The performance of BlueTrack was evaluated in the laboratory for its proximity prediction accuracy. In addition, two diary studies were used to evaluate the accuracy of BlueTrack in a more natural setting.

I also presented two research case studies that use PowerLine Positioning and BlueTrack as an investigational tool. With these two deployment studies, I showed the type of studies these technologies enabled, the deployment issues of the technologies, the quality of the automatically gathered quantitative data compared to traditional self-report methods, and the improvement of the quality of data when applying the mixed-method approach using the tracking data.

The first study was an in-depth empirical investigation of the proximity of the mobile phone to its owner over several weeks of continual observation. The aim of this study was to determine if the mobile phone was a suitable proxy for its owner, understand the reasons behind separation between user and the mobile phone, and offer guidelines for building mobile phone applications. From this study, I showed that BlueTrack offered several key advantages. It allowed the continuous recording of the user's distance to their phone and the gathering of quantitative data not otherwise possible with other investigational means. Additionally, the quantitative data I was able to collect allowed me to explore whether it was possible to apply machine learning techniques to the proximity behavior. Finally, there was little modification to the user's natural behavior during the investigation, and the resulting quantitative proximity traces proved valuable during the mixed-method interview process and the final analysis.

The second study was the deployment of PowerLine Positioning to study the activity of wheelchair users in their homes. In collaboration with researchers at the Center for Assistive Technology and Environmental Access (CATEA) at Georgia Tech, I conducted a study of that looked at mobility patterns of wheelchair users in the home. The aims were to determine the in-home environmental factors that promote or hinder mobility, where users spend much of their time in the home, locations where users do not go, and when and where they transition between multiple ambulatory devices. I used

PowerLine Positioning to collect data on the usage of ambulatory and mobility devices in the home. I also used this data to obtain a more detailed and objective understanding of mobility patterns over a long period of time and used the gathered location data to conduct more effective interviews with the participants. I also showed that the mixed-method approach resulted in finding more environmental barriers and mobility issues in the home when compared to the current best practice of self-report. The mixed-method process also uncovered themes that otherwise would not have been found using their traditional approach. In addition, I also gathered an understanding of the deployment issues and challenges of PowerLine Positioning in terms of installation and removal time and its ease of use for the researcher compared to existing approaches.

PowerLine Positioning (PLP) is a promising indoor positioning system for the home that uses its powerline infrastructure and requires only the addition of two plug-in modules to the home infrastructure and the use of simple location tags. The system is capable of localizing to sub-room level precision using a fingerprinting technique on the amplitude of tones produced by the two modules installed in extreme locations of the home. The density of electrical wiring at different locations throughout the home provides a time-independent spatial variation of signal propagation.

The critical analysis of PLP and the experimental validation in many different homes suggests the following advantages over current indoor location solutions:

- PLP leverages a truly ubiquitous resource, the powerline infrastructure, available in almost all homes. PLP requires very minimal addition to the infrastructure (two plug-in modules).

- It achieves superior sub-room-level classification, with an accuracy of 93% on average up to a meter resolution and does not detract from the appearance of the home.

The next step is to build smaller, less expensive, and lower powered tags for practical deployments of PLP. In addition, I plan to incorporate other spatially varying signal features, such as phase differences between the tones in addition to the amplitude to increase the accuracy and resolution of PLP in the fingerprinting process. Further stability analysis is also planned to determine the full viability of PLP.

The classification of an important new class of activity monitoring systems that I call ***infrastructure mediated sensing (IMS)*** is poised to provide a new set of enabling technologies that will support practical and large-scale deployments of activity and location sensing systems. PLP falls within this class of sensing systems. In this dissertation, I also discussed two additional technologies aimed at acquiring activity information for minimal instrumentation of the environment and further demonstrates this IMS concept.

I presented an approach for a low-cost and easy-to-install PowerLine Event Detection system that is capable of identifying certain electrical events, such as switches that are toggled. This system has implications for applications seeking simple activity detection, home automation systems, and energy usage information. I showed how the system learns and classifies unique electrical events with high accuracy using standard machine learning techniques. Additionally, a deployment of the system in several homes showed long-term stability and the ability to detect events in a variety of different types of homes. I also discussed specific events the system can detect and which events may have problems when used for specific applications. The system has the potential to be integrated easily into existing applications that aim to provide services based on detection of various levels of activity.

I have also developed an approach for whole-house gross movement and room transition detection through sensing at only one point in the home. I consider this system to be one member of an important new class of human activity monitoring approaches based on infrastructure mediated sensing, or "home bus snooping.” My solution leverages the existing ductwork infrastructure of central heating, ventilation, and air conditioning (HVAC) systems found in many homes. Disruptions in airflow caused by human inter-room movement result in static pressure changes in the HVAC air handler unit. This is particularly apparent for room-to-room transitions and door open/close events involving partial blockage of doorways and thresholds. I detect and record this pressure variation from sensors mounted on the air filter and classify where certain movement events are occurring in the house, such as an adult walking through a particular doorway or the opening and closing of a door. Although less precise, I also show the detection of movement when the HVAC is not operating. In contrast to more complex distributed sensing approaches for motion detection in the home, the method requires the installation of only a single sensing unit.

The combination of different types of infrastructure mediated sensors offers a number of attractive properties for deployment of useful applications in the home. For example, the combination of detecting human-initiated electrical or water events with the work on movement detection through airflow sensing enables a variety of new approaches for integrating energy and environmental conservation with ordinary human activities in the home. A system could alert an individual that he or she should attend to an energy or environmental conservation task, such as turning off an unneeded light or a running faucet, when the system detects that he or she is near that part of the house. The combination of electrical event detection and airflow detected movement information can also provide important correlation data for energy conservation applications by relating a person's usage of the physical space with the usage of electrical devices. One could design an energy-efficient zoned HVAC unit that selectively heats or cools each zone on the basis of activity information passively sensed through the HVAC system itself, which would offer a tremendous installation and maintenance cost benefit over competing distributed sensing approaches.

APPENDIX A

WHEEL CHAIR MOBILITY STUDY MATERIALS

A.1 Home Accessibility Survey (HAS)

This is an example of the current practice self-report survey used in the mobility disability community called the Home Accessibility Survey (HAS). Only the relevant subset of the survey (Section III about in-home mobility) has been included.

ee. Maneuvering PMD	Are you able to position your wheelchair well enough to transfer?
2. Sufficient Assistance	If you use assistance when transferring, is it adequate for your needs?
B. Reach	Can you easily reach the items you need in your home, for example, items sitting in the back of kitchen countertops or on a table?
1. Surface Barriers	Do the surfaces in your home, such as tabletops and countertops, allow you to easily reach items you want?
2 Physical/Health Problems	Do you experience fatigue or pain when reaching for items?
aa. Fatigue	Do you experience fatigue when reaching for an item?
bb. Pain	Do you experience pain when reaching for an item?
3. Sufficient Assistance w/ WC	If you use assistance when reaching, is it adequate for your needs?
III Indoor Home Accessibility	**Is your home accessible to you? (e.g., can you enter and exit your home easily, move between rooms, and do all the activities you need to do while at home?**
A. Entering and Exiting Home	**Are you able to enter and exit your home easily and comfortably?**
1. Doorways	Are doorways wide enough to enter and leave the home using your wheelchair?
2. Threshholds	Do the thresholds allow you to easily enter and leave your home?
3. Door jambs	Do the door jambs allow you to easily enter and leave your home
4. Stairs	If there are any stairs at the entrance to your home, do these impact your ability to enter and exit easily?
aa. Ramp	Is there a ramp at the entrance to your home that allows you to easily enter and leave your home?
bb. Elevator	Is there an elevator that makes the entranceway to your home accessible?
5. Floor Surfaces	Do the floor surfaces at the entranceway allow you to easily move in and out of your home?
B. Between Rooms	**Are you able to move between rooms easily and comfortably?**
1. Doorways	Are doorways wide enough for you to move inbetween rooms?
2. Thresholds	Do the thresholds between rooms allow you to enter and exit rooms?
3. Door jambs	Do door jambs allow you to enter and leave rooms?
4. Stairs	If there are any stairs in your home, do these impact your ability to move between rooms while you're in your wheelchair?
aa. Stairlifts	Do you have a stairlift to help move you between floors?
bb. Elevator	Do you have an elevator to help you move between different levels of your home?
cc. Chairlifts	Do you have a chairlift that lets you move between floors?
5. Floor Surfaces	Do floor surfaces make it difficult for you to move between rooms in your home?
6. Furniture	Is furniture positioned to make it easy for you to move between rooms when you're in your wheelchair?
C. Within Rooms	**Are you able to perform all the activities you want or need to in the rooms of your home (bathroom, living room, and sleeping area)**
1. Bathroom layout	**Do the design and layout of your bathroom make it easy to carry out your normal activities there?**
aa. Accessible Toilet	Is your toilet easily accessible to you?
bb. Accessible Shower/Tub	Is your shower accessible to you, for example, is it wide enough for you to get through in your wheelchair or a shower chair?
cc. Accessible Sink	Is your sink accessible to you, for example, is it high enough for your wheelchair to fit underneath.?
dd. Bathroom size	Is your bathroom big enough to accommodate your wheelchair easily?
ee. Bathroom modifications	Is your bathroom adequately modified to make it easy and safe for you to perform your routine activities there (for example, grab bars)?
ff. Floor surfaces	Does floor surface in your bathroom allow you to easily move around?
2. Living area layout	**Do the overall design and layout of your living area allow you to carry out your normal everyday activities easily?**
aa. Furniture/Household Objects	Are furniture and household objects placed so as to make it easy to maneuver around your living area?

bb. Floor surfaces	Do floor surfaces in your living area allow you to easily move around?
cc. Table or countertop height	Are tables and countertops accessible to you while sitting in your wheelchair?
dd. Living area size	Is your living area big enough to accommodate your wheelchair easily?
c. Sleeping area layout	**Do the design and layout of your sleeping area make it easy for you to get enough rest and sleep?**
bb. Floor surfaces	Does the floor surface in your sleeping area allow you to move around easily?
cc. Chest/Table height	Do chest and/or table heights allow you to perform routine activiities (for example, turning out a light, leaving something on a table).
dd. Closet Accessibility	Are contents of your closets accessible to you?
IV Outdoor Home Accessibility	**Do you feel you have access to those outdoor areas around your home that are important to you?**
A. Outdoor accessibility	**Do the design and layout of outdoor areas around your home allow you to easily move around?**
1. Yard/Deck/Grounds	Is your yard/deck/grounds accessible to you?
2. Garage	If you have a garage, is it accessible to you?
3. Indoor/Outdoor entrances	Are entrances to outdoor areas around your home accessible to you?
B. Outdoor ground surfaces	**Do ground surfaces in outdoors areas around your home allow you to get around easily in your wheelchair?**

A.2 Exit Survey

Wheelchair Mobility Study – Exit Survey

Please circle a value the 1-5 scale for the following questions:

1. The tag was comfortable to wear.

Strongly Agree--- 1 2 3 4 5 ---Strongly Disagree

2. I found that the location system was aesthetically unappealing in my home.

Strongly Agree--- 1 2 3 4 5 ---Strongly Disagree

3. I had recharge the location tags often.

Strongly Agree--- 1 2 3 4 5 ---Strongly Disagree

4. I often forgot to wear my tag.

Strongly Agree--- 1 2 3 4 5 ---Strongly Disagree

5. I found the tags on the mobility aids distracting.

Strongly Agree--- 1 2 3 4 5 ---Strongly Disagree

APPENDIX B

POWERLINE POSITIONING DETAILS AND SCHEMATICS

This appendix includes PowerLine Postioning (PLP) system functional specifications, block diagrams, parts, and schematics.

B.1 Receiver Tag Specifications

- **Overview:** The receiver tag must detect two mid frequency (500 kHz and 600 kHz) AM modulated signals and extract the amplitude (signal strength) for each and wirelessly transmit back those two values along with an unique ID via an on board RF transmitter to a personal computer.
- Minimally, the tag should detect and transmit the signal strengths every 100 ms (10 Hz).
- The tag will have a low power Bluetooth or Zigbee radio that is capable of transmitting the detected signal strengths back to a RF receiver connected to a personal computer up to 50 ft away.
- Minimally, the detected signal strengths must have a resolution of 10 bits each.
- Each data transmission unit from the tag consists of a 16 bit unique ID, two 10 bit signal values, and a single bit indicating if the button on the tag is being pressed.
- The RF receiver connected to the personal computer should be able to receive data from up to 7 tags. An application running on the personal computer will handle the fingerprinting algorithm and provide location services to other applications.
- Ideally, the receiver's antenna is entirely omni-directional and fit within the specified physical size constraints. Omni-directional in two dimensions would be acceptable.
- The tag should last approximately 7 days on a single charge. The tag will go into a standby mode when no motion is present for 30 seconds and reactivate itself when motion is detected by an onboard mechanical motion switch.
- The tag will have a small charging port where an AC charging adaptor will plug in.
- The tag will have an on/off switch and a single button. The button will be used indicate a special action to the remote computer. Currently the intended use is during

the calibration process to tell the personal computer to store the current values to the fingerprint database.

Physical Specifications:

- Size: 1.5” X 2.0” X 0.5” (including battery)
- Weight: < 30g

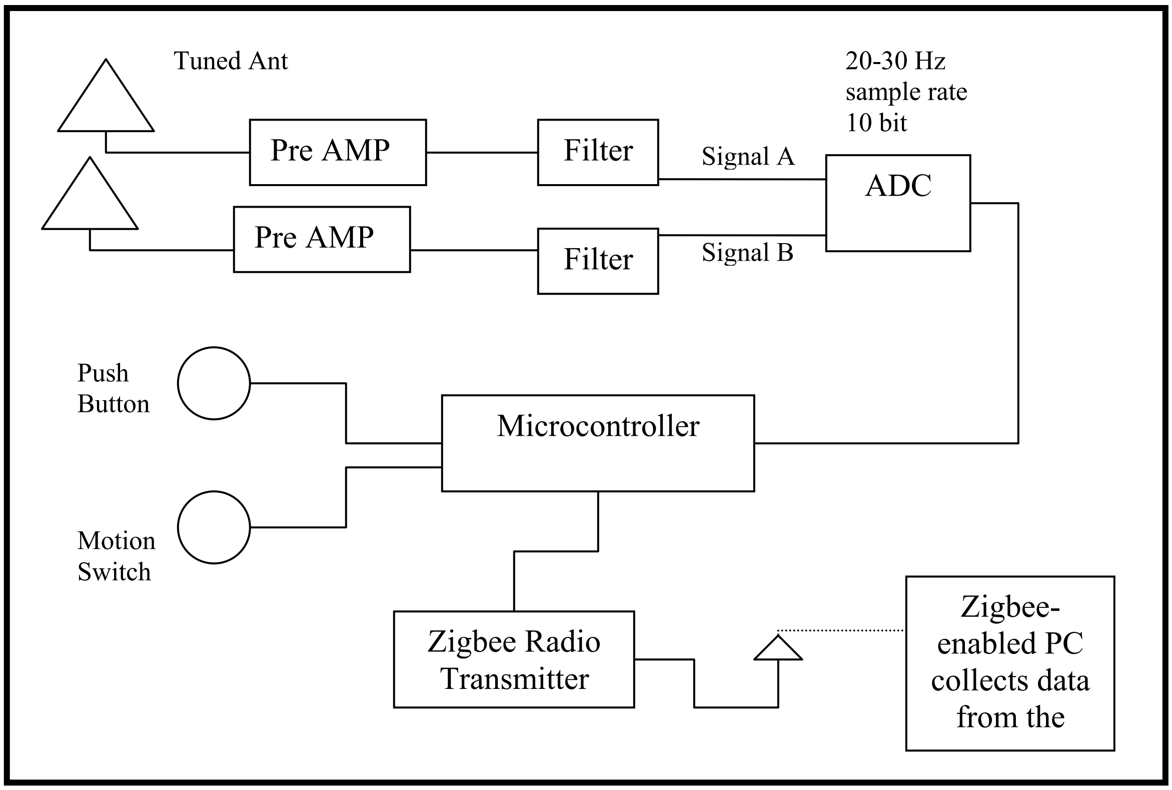


Figure 47: High-level block diagram of the PLP location tag

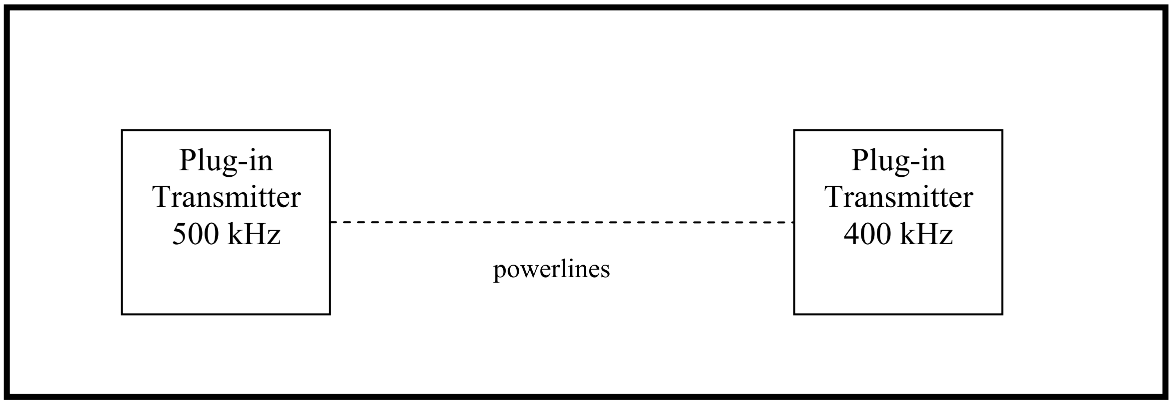


Figure 48: High-level block diagram of the power line injector and signal generation system

B.2 PLP Hardware Schematics and Components

The PLP hardware circuit diagrams, schematics, and components are shown for the different versions used in experiments.

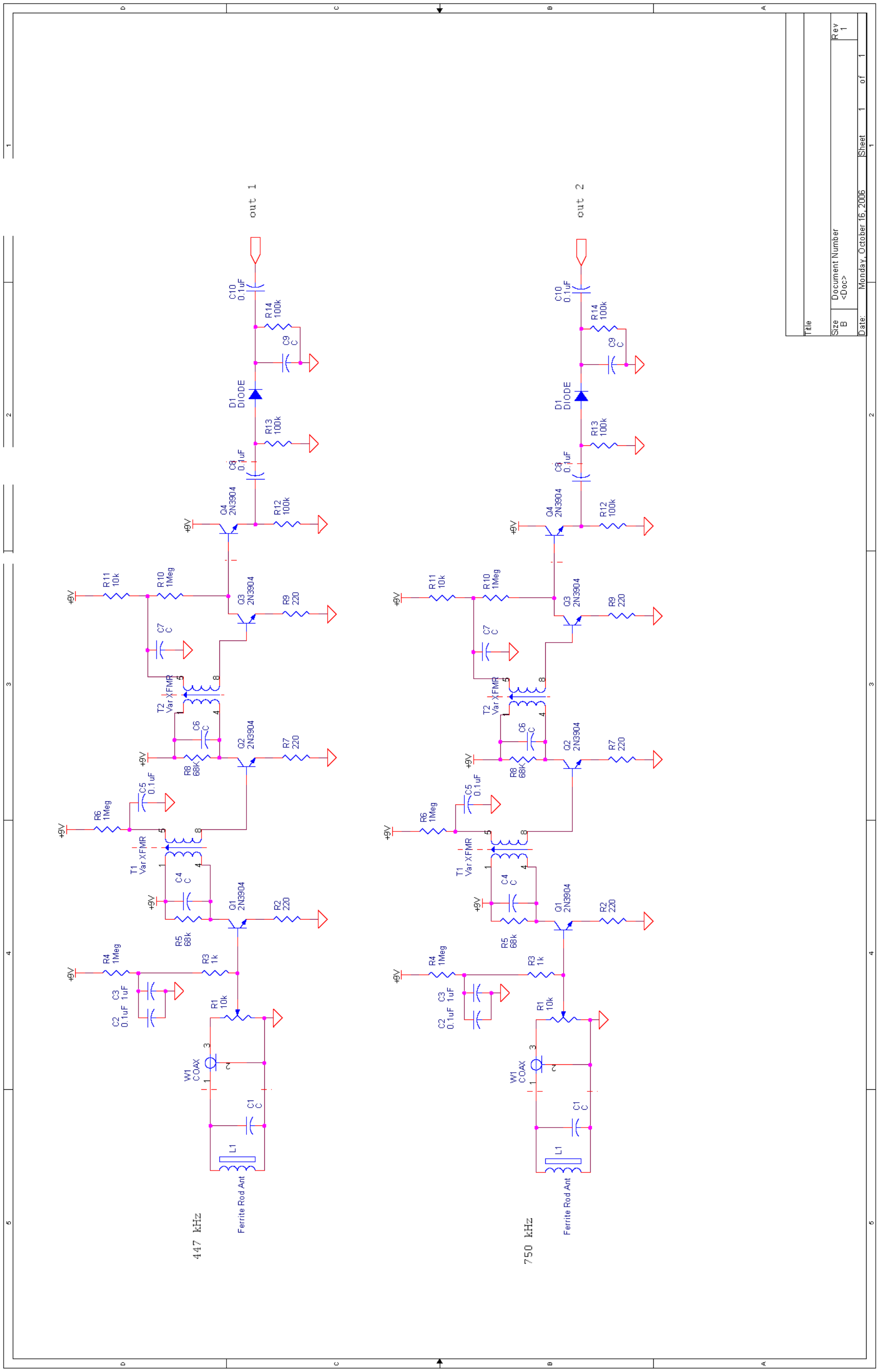


Figure 49: First generation PlowerLine Positioning front-end tag schematics

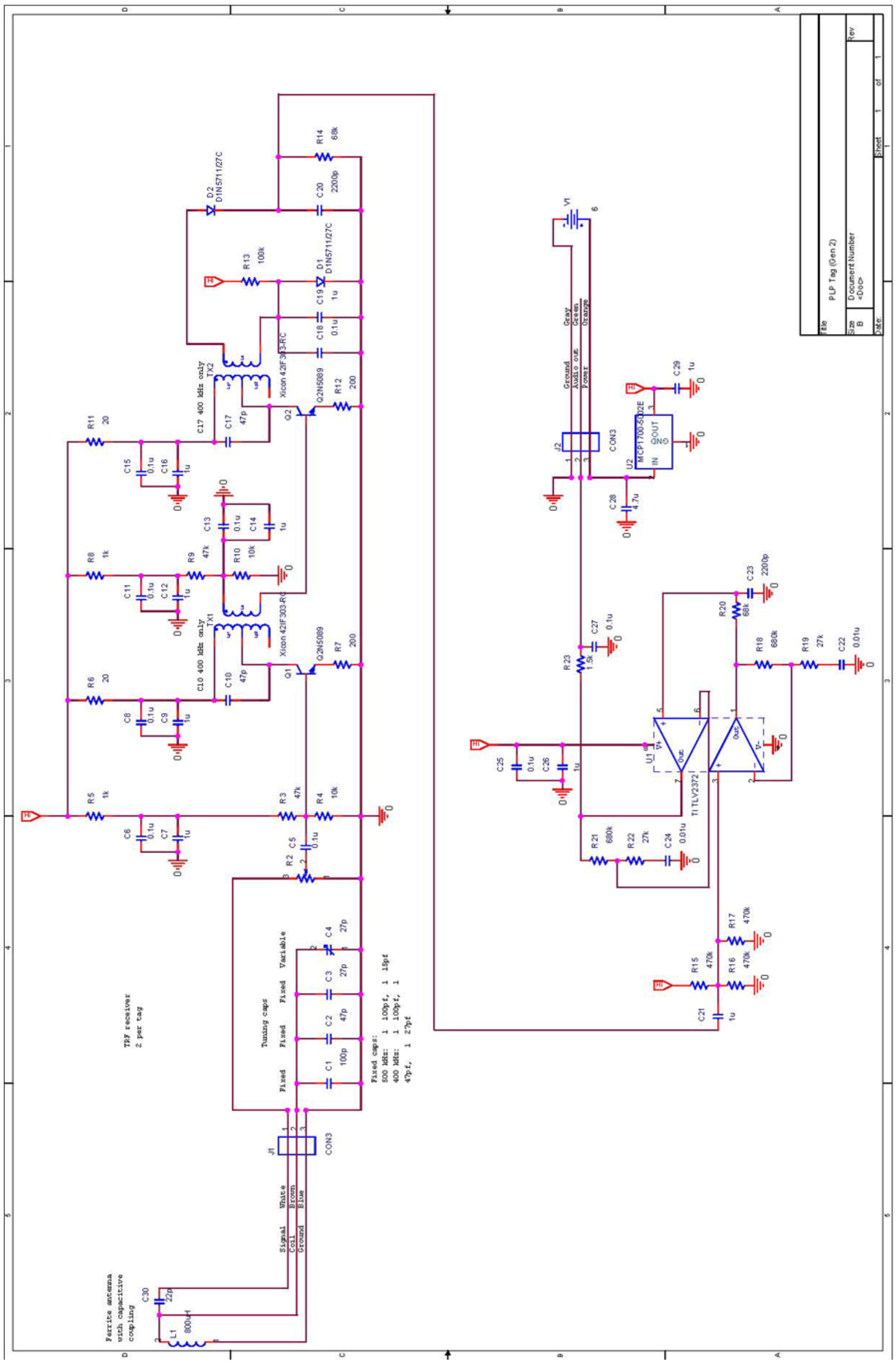


Figure 50: Second generation PlowerLine Positioning front-end tag schematics

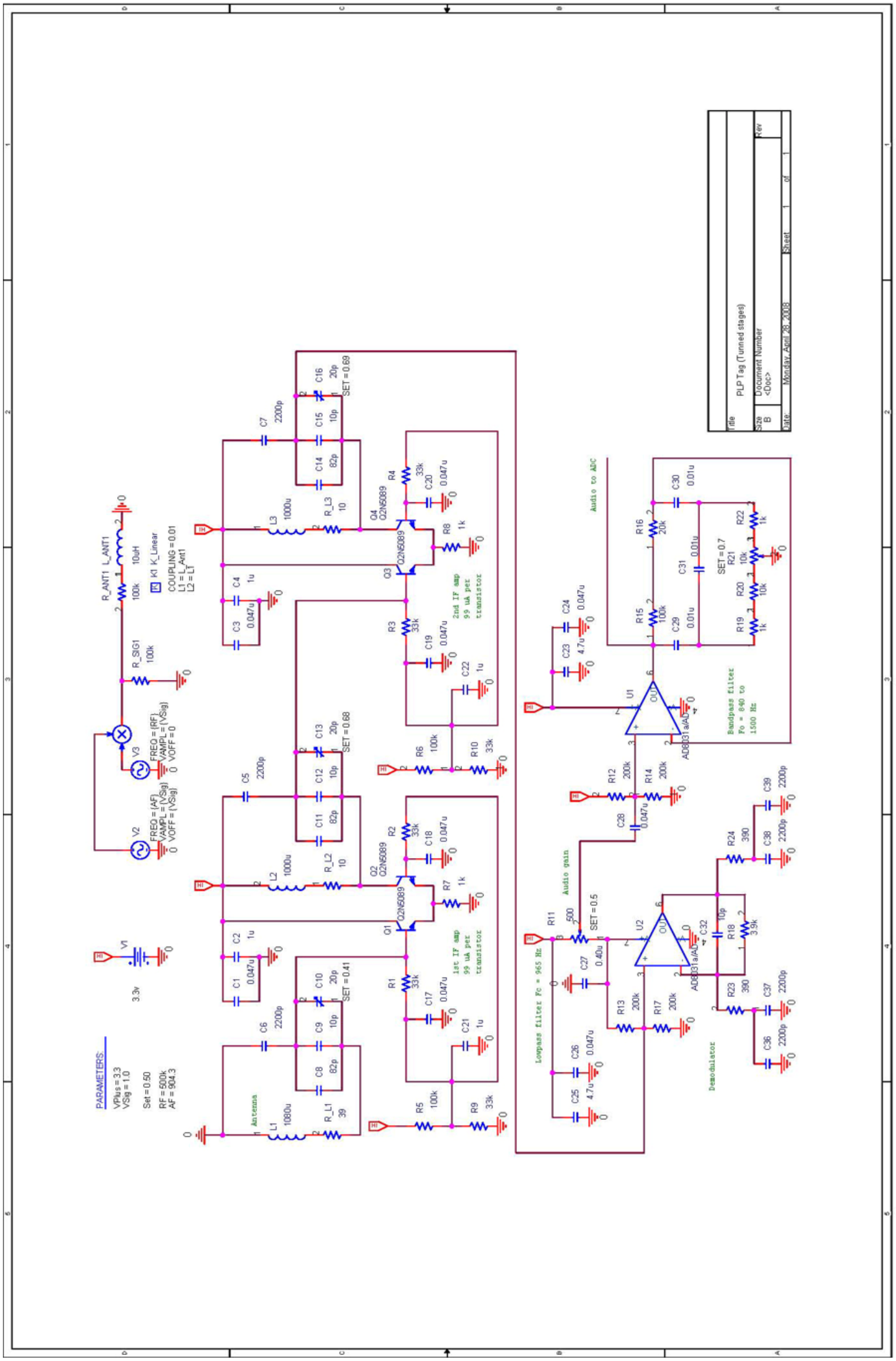


Figure 51: Third generation PlowerLine Positioning tag schematics

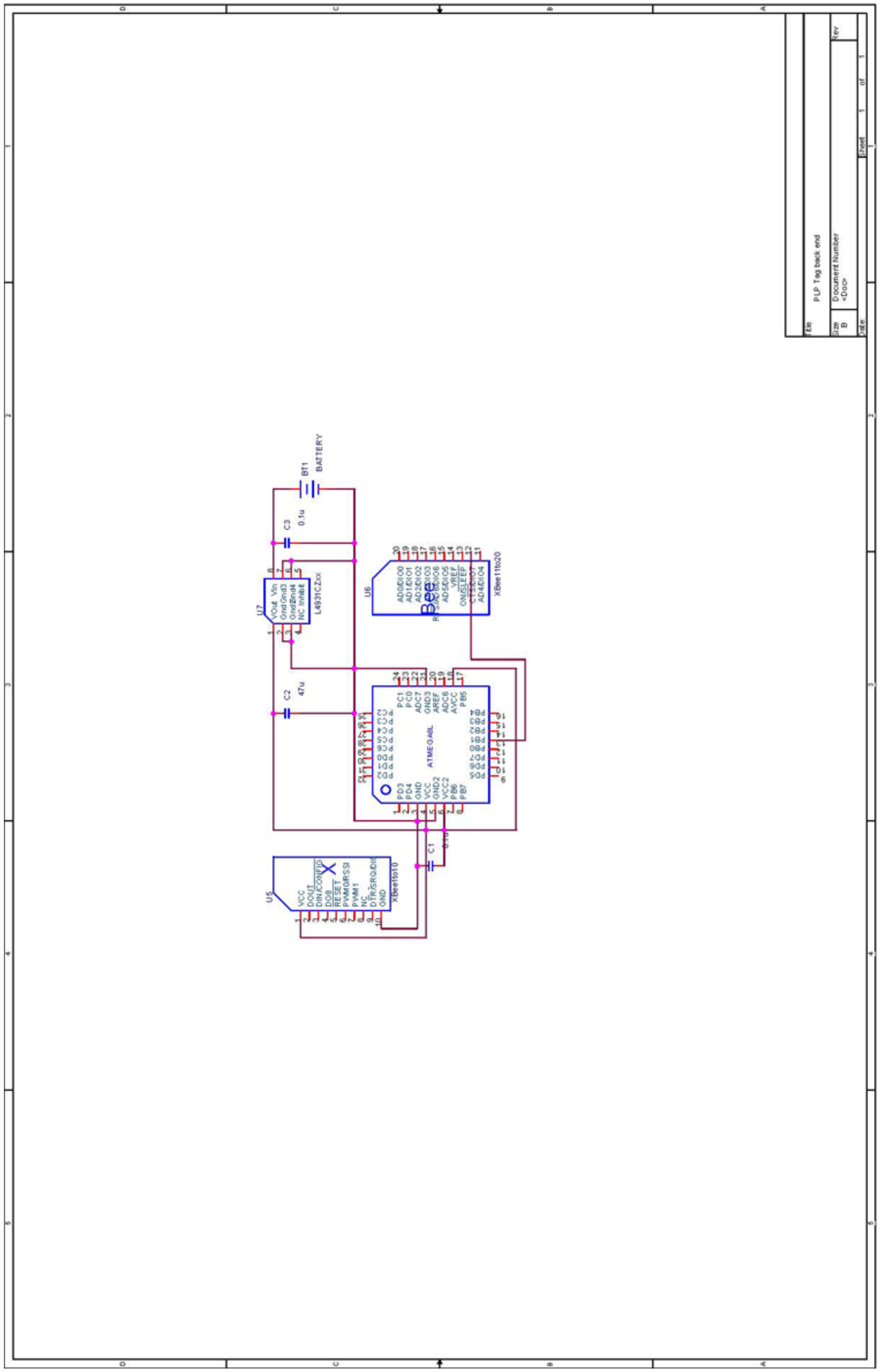


Figure 52: PowerLine Positioning wireless Zigbee back channel

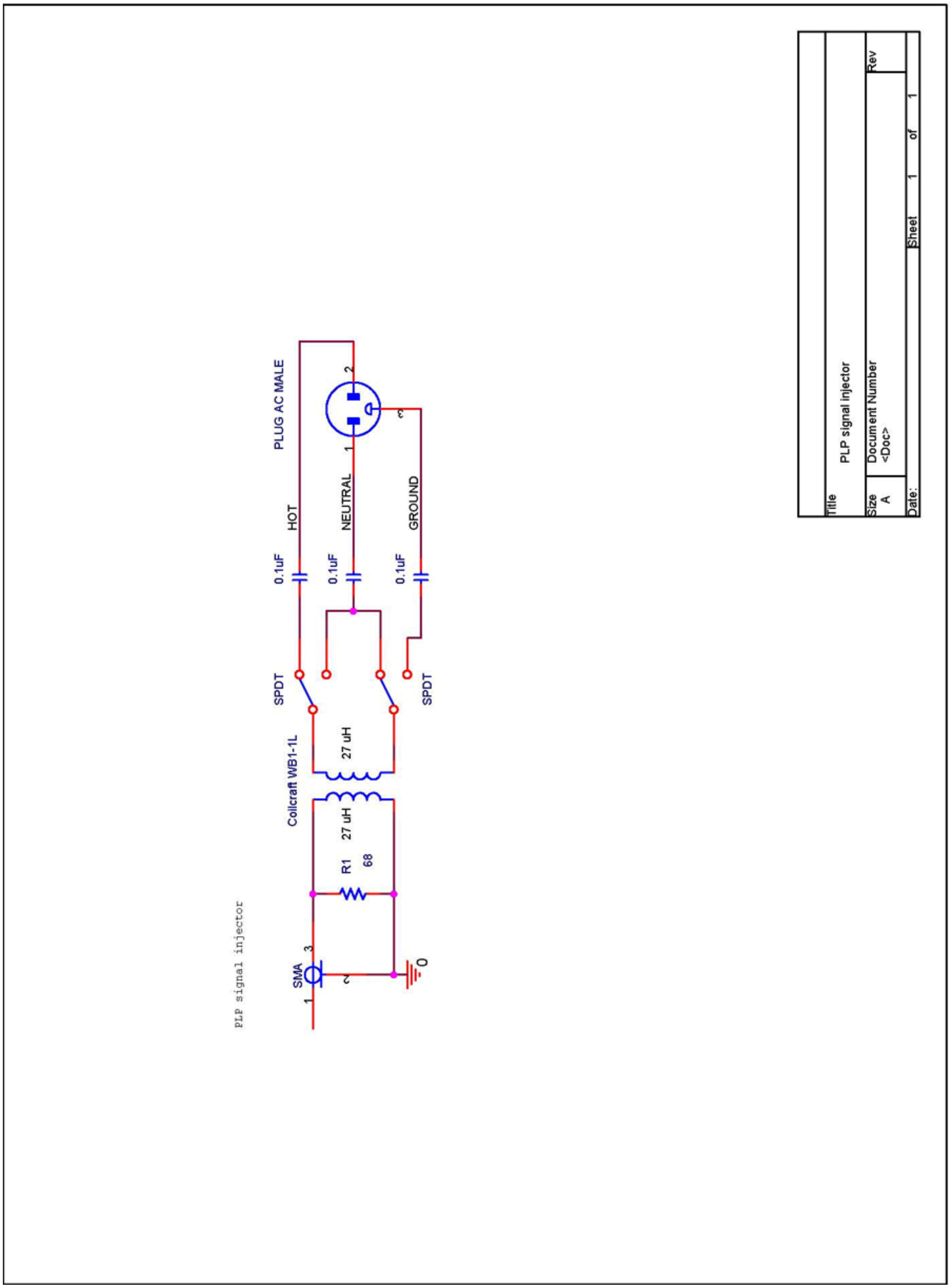


Figure 53: Experimental power line signal injector

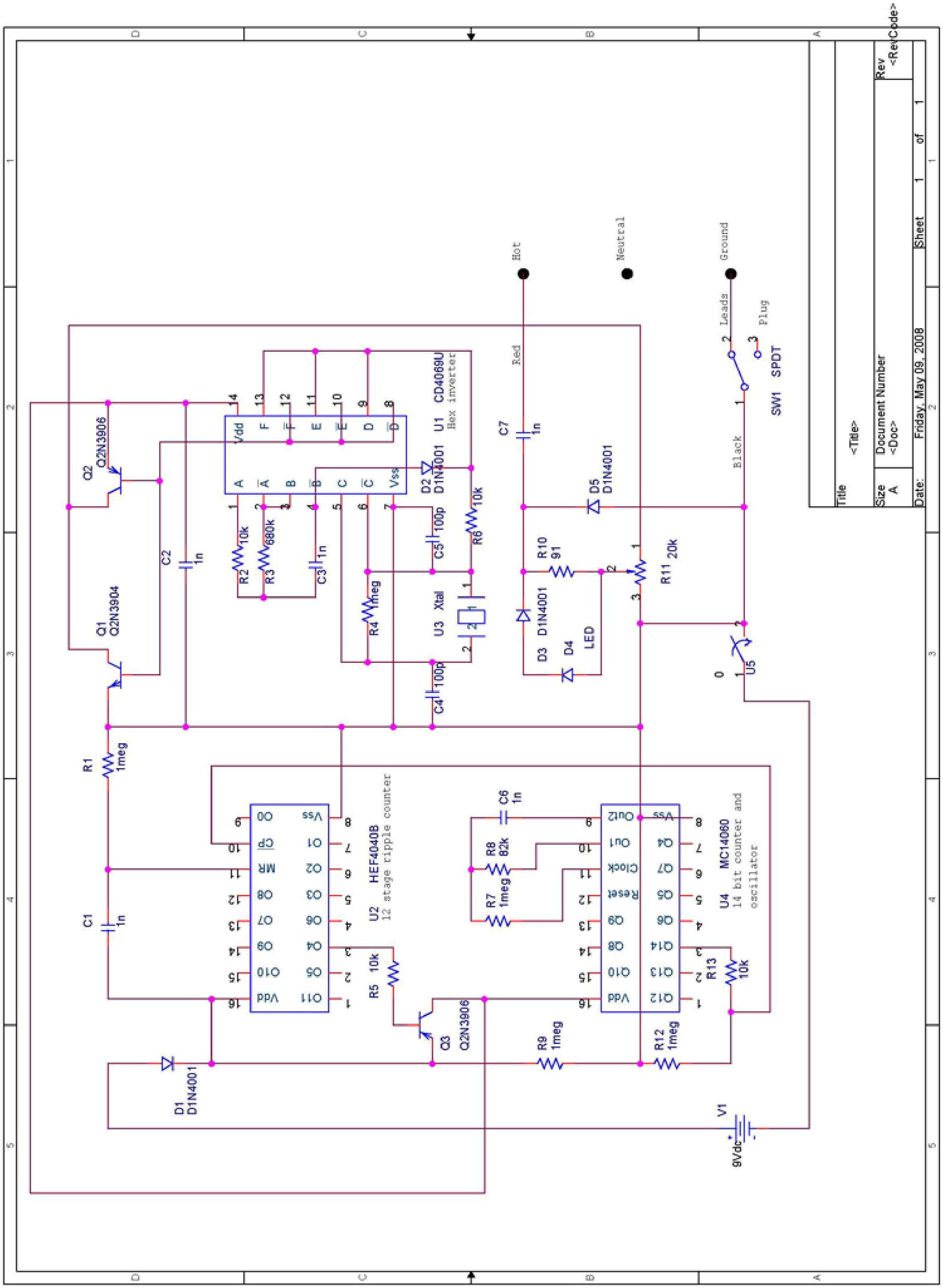


Figure 54: Plug-in power line signal injector module

Gen 2 PLP Tag Parts and Reference Numbers

C_C14 0 N787285 1u

Q_Q2 N787809 N787429 N7849382 Q2N5089

R_R23 N948935 N938109 1.5k

R_R10 0 N787285 10k

R_R8 N859537 $D_HI 1k

D_D1 N831989 0 D1N5711/27C

C_C4 0 N778685 {27p*0.5+.001p}

C_C23 0 N945859 2200p

C_C3 0 N778685 27p

R_R12 N7849382 0 200

R_R21 N949324 N948935 680k

X_TX2 N787868 N787809 M_UN0001 N831501 N831989 XFRM_LIN/CT-PRI PARAMS:

+ LP1_VALUE=485u LP2_VALUE=194u LS_VALUE=99u COUPLING=.99 RP_VALUE=6.1

+ RS_VALUE=0.89

C_C7 N857427 0 1u

C_C27 0 N938109 0.1u

R_R9 N787285 N859537 47k

C_C5 N780212 N7797102 0.1u

R_R13 N831989 $D_HI 100k

C_C11 0 N859537 0.1u

C_C20 0 N832871 2200p

R_R18 N945127 N944897 680k

C_C21 N832871 N918546 1u

X_R2 0 N779902 N7797102 SCHEMATIC1_R2

C_C19 0 N831989 1u

X_TX1 N782421 N935017 M_UN0002 N787285 N787429 XFRM_LIN/CT-PRI PARAMS:

```
+  LP1_VALUE=485u LP2_VALUE=194u LS_VALUE=99u COUPLING=.99
RP_VALUE=6.1
+  RS_VALUE=0.89
C_C18         0 N831989  0.1u
C_C28         0 N930391  4.7u
Q_Q1         N935017 N780212 N7809392 Q2N5089
C_C13         0 N787285  0.1u
R_R11         N787868 $D_HI  20
R_R3         N857427 N780212  47k
R_R15         N918546 $D_HI  470k
C_C10         N935017 N782421  47p
R_R4         0 N780212  10k
R_R16         0 N918546  470k
R_R6         N782421 $D_HI  20
R_R22         N8467751 N949324  27k
C_C15         0 N787868  0.1u
V_V2         N864365 0
+SIN 0.5 1 1000 0 0 0
E_MULT1         M_UN0003 0 VALUE {V(N864365)*V(N801851)}
D_D2         N831501 N832871 D1N5711/27C
R_R19         N8388261 N945127  27k
C_C2         0 N778685  47p
C_C29         0 $D_HI  1u
C_C12         0 N859537  1u
C_C16         0 N787868  1u
R_R5         N857427 $D_HI  1k
C_C6         N857427 0  0.1u
R_R17         0 N918546  470k
C_C17         N787809 N787868  47p
R_R7         0 N7809392  200
C_C26         0 $D_HI  1u
```

```
V_V3         N801851 0
+SIN 0 1 500k 0 0 0
C_C22         0 N8388261  0.01u
C_C8         0 N782421  0.1u
R_R14         0 N832871  68k
C_C24         0 N8467751  0.01u
C_C9         0 N782421  1u
C_C1         0 N778685  100p
R_R20         N944897 N945859  68k
V_V1         $D_HI 0 6
C_C25         0 $D_HI  0.1u
X_U2         N930391 $D_HI 0 LAS1505

.subckt SCHEMATIC1_R2 1 2 t
RT_R2         1 t {(10K*(1-0.9))+.001}
RB_R2         t 2 {(10K*0.9)+.001}
.ends SCHEMATIC1_R2
```

Gen 3 PLP Tag Parts and Reference Numbers

```
R_R2        N2190243 N2178021  33k
Q_Q3        $D_HI N2157445 N2185257 Q2N5089
R_R8        0 N2185257  1k
C_C28        N2090691 N2088607  0.047u
Q_Q4        N1807814 N2189450 N2185257 Q2N5089
R_R9        0 N2178021  33k
R_R19        N2091207 N20914200  1k
R_R5        N2178021 $D_HI  100k
V_V3        N2109202 0 DC 0 AC {VSig}
+SIN 0 {VSig} {RF} 0 0 0
X_U2        N1847863 N1860215 N1858229 0 N1860062 AD8031a/AD
R_R15        N2091116 N2091149  100k
R_R16        N2091149 N2091267  20k
V_V1        $D_HI 0 3.3v
X_R21    N20907511 N20907510 0 SCHEMATIC1_R21
R_R_ANT1        N14039770 N2106648  100k
C_C16        N1807814 N1847863 {20p*0.69+.001p}
C_C23        0 $D_HI  4.7u
C_C17        0 N2178021  0.047u
C_C39        0 N2255391  2200p
L_L1        0 N16469880  1080u
E_MULT1        N2106648 0 VALUE {V(N1226589)*V(N2109202)}
R_R18        N1860215 N1860062  3.9k
C_C24        0 $D_HI  0.047u
C_C36        0 N2255851  2200p
R_R20        N20914200 N20907511  10k
R_R13        N1847863 N1858229  200k
R_R_L3        N1807814 N14047291  10
C_C29        N2091207 N2091116  0.01u
R_R24        N2255391 N1860062  390
```

```
C_C2         0 $D_HI  1u
C_C18         0 N2190243  0.047u
R_R4         N2189450 N2188210  33k
C_C26         0 $D_HI  0.047u
R_R17         0 N1847863  200k
C_C10         N1667971 N1994091 {20p*0.41+.001p}
C_C30         N2091237 N2091267  0.01u
L_L2         N21337160 $D_HI  1000u
Q_Q1         $D_HI N1994091 N2142460 Q2N5089
C_C1         0 $D_HI  0.047u
C_C12         N2157401 N2157445  10p
C_C20         0 N2189450  0.047u
L_L_ANT1         N14039770 0  10uH
R_R6         N2188210 $D_HI  100k
Q_Q2         N2157401 N2190243 N2142460 Q2N5089
C_C15         N1807814 N1847863  10p
C_C9         N1667971 N1994091  10p
C_C38         0 N2255391  2200p
Kn_K1         L_L_Ant1 L_L1     0.01
C_C31         N2091237 N2091207  0.01u
R_R12         N2088607 $D_HI  200k
R_R_L2         N2157401 N21337160  10
C_C6         N1994091 0  2200p
C_C4         0 $D_HI  1u
C_C11         N2157401 N2157445  82p
R_R7         0 N2142460  1k
C_C32         N1860215 N1860062  10p
R_R10         0 N2188210  33k
C_C21         0 N2178021  1u
L_L3         $D_HI N14047291  1000u
C_C14         N1807814 N1847863  82p
```

```
C_C8         N1667971 N1994091  82p
X_R11    N1858229 $D_HI N2090691 SCHEMATIC1_R11
R_R22         N20907510 N2091237  1k
R_R14         0 N2088607  200k
C_C5         $D_HI N2157445  2200p
C_C22         0 N2188210  1u
C_C3         0 $D_HI  0.047u
C_C37         0 N2255851  2200p
C_C7         N1847863 $D_HI  2200p
C_C19         0 N2188210  0.047u
R_R_SIG1         N2106648 0  100k
R_R23         N2255851 N1860215  390
C_C13         N2157401 N2157445 {20p*0.68+.001p}
C_C25         0 $D_HI  4.7u
C_C27         N1858229 0  0.40u
R_R1         N2178021 N1994091  33k
R_R_L1         N1667971 N16469880  39
V_V2         N1226589 0 DC {VSig} AC {VSig}
+SIN {VSig} {VSig} {AF} 0 0 0
R_R3         N2188210 N2157445  33k
X_U1         N2088607 N2091267 $D_HI 0 N2091116 AD8031a/AD
.PARAM  AF=904.3 RF=500k VPlus=3.3 VSig=1.0 Set=0.50

.subckt SCHEMATIC1_R21 1 2 t
RT_R21         1 t {(10k*(1-0.7))+.001}
RB_R21         t 2 {(10k*0.7)+.001}
.ends SCHEMATIC1_R21

.subckt SCHEMATIC1_R11 1 2 t
RT_R11         1 t {(500*(1-0.5))+.001}
RB_R11         t 2 {(500*0.5)+.001
```

B.3 PowerLine Positioning Hardware Performance

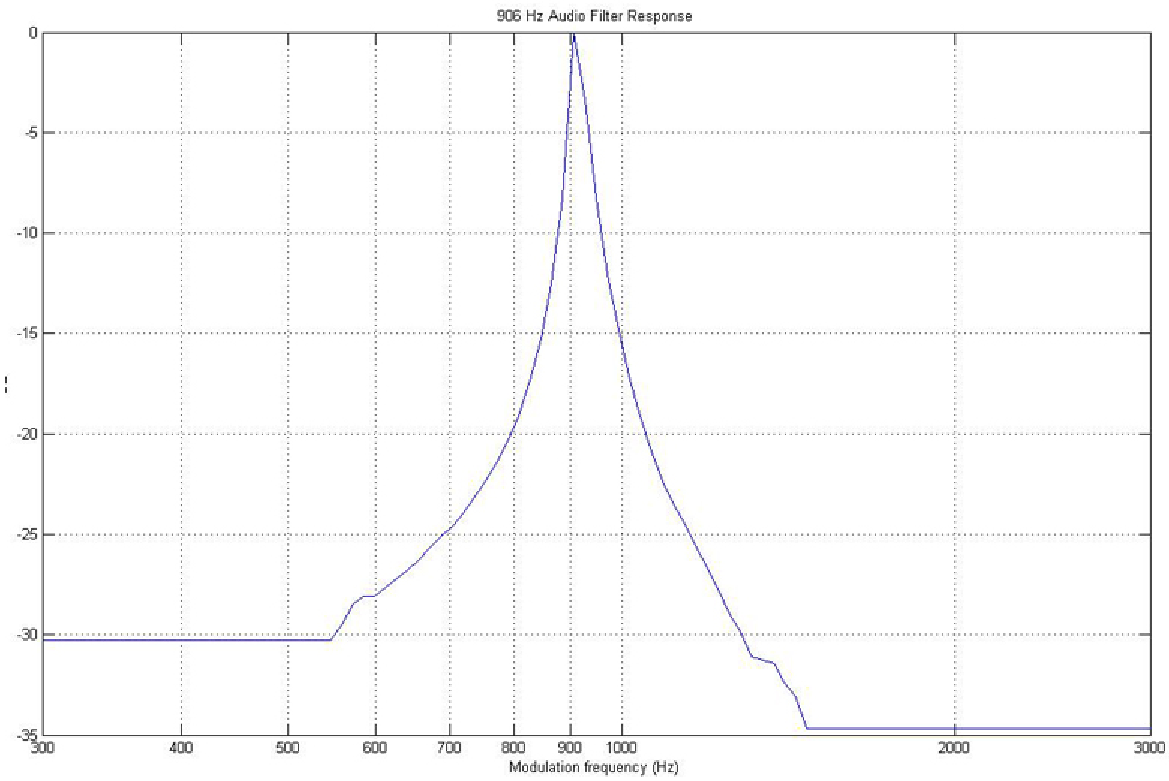


Figure 55: Frequency response of PLP location tag during the bench top experiments.

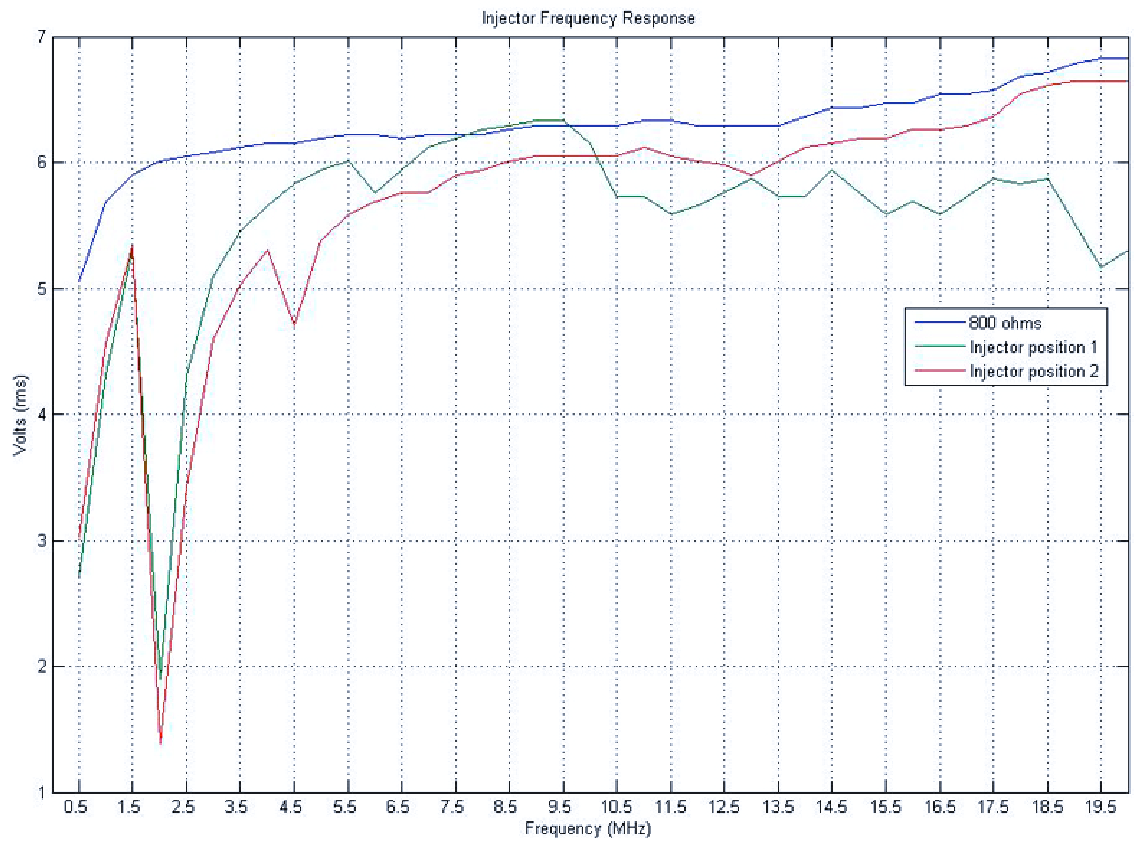


Figure 56: PLP plug-in injector module frequency response at two difference locations in a single house. The results of an 800 ohm impedance is also shown for reference.

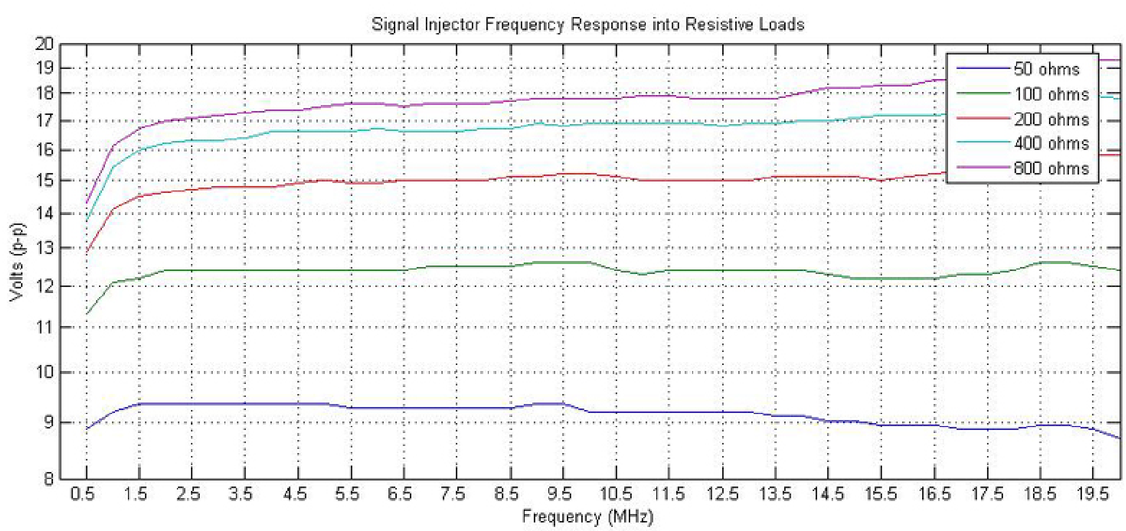


Figure 57: PLP plug-in injector module frequency response at various input impedance loads.

B.4 PowerLine Positioning Installation Manual

This section includes the PLP manual for installing and calibrating the tracking hardware. The instructions on using the tracking software and visualization tools are also included.

PLP Configuration Tool Manual

1. 2 Separate Applications

The tool has 2 applications:

a. Configuration Tool
b. Visualization Tool

2. Configuration: Main Screen

This is the main screen of the Configuration Tool. Here you can add and edit floorplans and manage the objects/inhabitants and calibration for a building.

3. Adding a new building.

Click on 

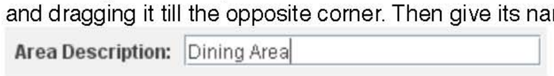
Type in the name of the building:

Attach floorplan: 

4. Drawing the floorplan.

Once you have added the floorplan image, the application would take you to the following screen:

Here you can add different area like Kitchen, Office, etc. The areas are supposed to be rectangular in shape. Use mouse to draw a rectangle by clicking on one corner and dragging it till the opposite corner. Then give its name/description in



Then, click 

Once you have added all the areas, click 

.

5. Editing a floorplan

Click on 

Select the appropriate building:

Edit the floorplan:

The size of an area can be changed by selecting it and dragging the edges. *(Kitchen in selected in the above image).*

nd giving it a name in

Make sure that you click on 

This commits changes in to the database.

6. Adding floorplan
If you need to add a floor to a building, then
Click on 

Select the appropriate building:

Click on 

and follow the same procedure as in a new building.

Click on 

.

7. Deleting a floorplan
If you need to delete a floor from a building, then
Click on 

Select the appropriate building:

Click on 

and currently active floor would be deleted.

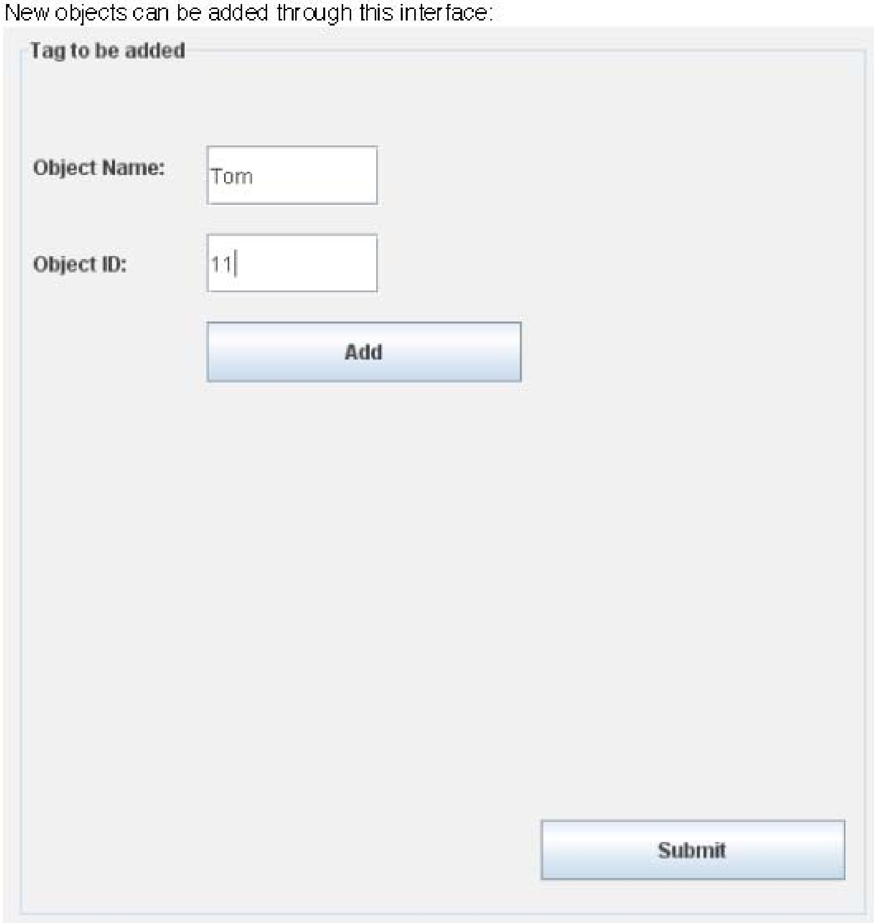
Click on 

.

9. Managing Objects of a building
If you need to manage inhabitants/objects of a building then,
Click on 

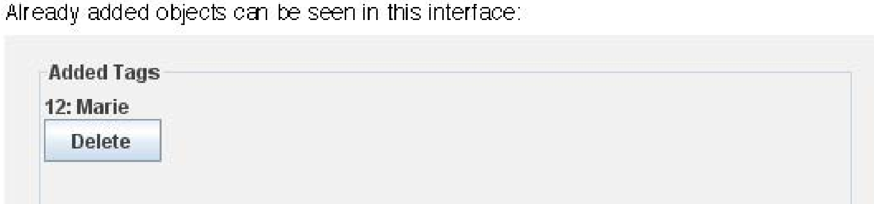
Select the appropriate building:

New objects can be added through this interface:



Give the name and ID(required for data logging) of the object and its tag and click ADD.
Click on Submit

Already added objects can be seen in this interface:



You can click on Delete to delete any of these objects.

10. Calibrating a building

When you are required to calibrate the system for a specific building.

Click on Calibration

Select the appropriate building:

The following screen would appear:

Different tabs represent different floors of the building.
To record signals for a particular area, click inside that area *(Kitchen is selected in the supplied image).* Then click on Calibrate . The system would calibrate itself for this area and record its signal strength. The same would also be shown in the "Received Signal" area of the interface.

Note: You can record multiple entries for any area, this allows you to calibrate an area for all possible orientations of the tag/object.

In case the entries for an area are recorded incorrectly, the user can click on:
Reset Data to reset the values for the selected area in the floorplan.

PLP Visualization Tool Manual

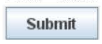
1. 2 Separate Applications

The tool has 2 applications:

a. Configuration Tool
b. Visualization Tool

2. Visualization: Building Selection

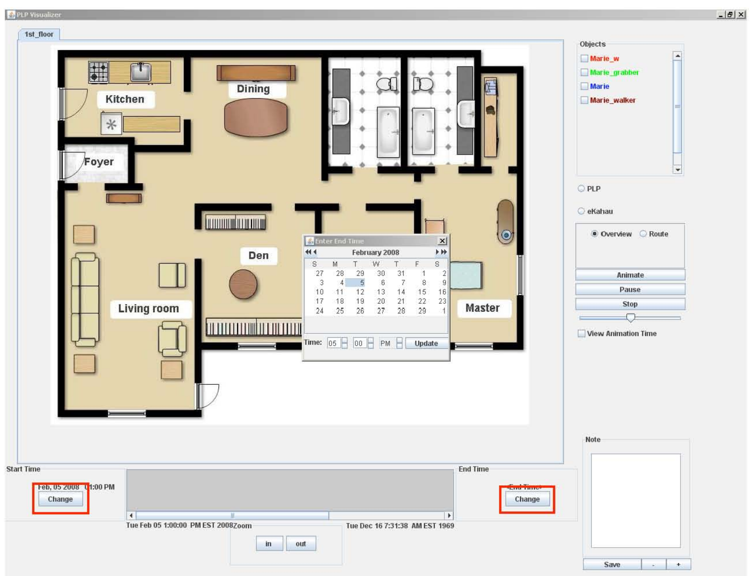
Firstly, user needs to select a building whose data needs to be visualized. The first screen of the tool would look like this:

The user can select the appropriate building from the drop down list and click: 

3. Time Period Selection

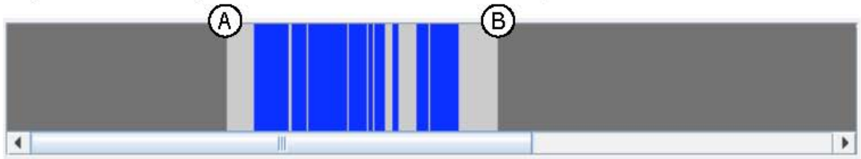
The tool requires the user to specify a start and end time of the data that needs to be visualized. This can be done by clicking on 2 highlighted 

buttons in the interface shown below.



4. Sub-Time Period Selection

In order to give the user a greater control over what data s/he is visualizing, the option to select a portion of time from the timeline is provided.



In the above figure you can see that a portion of the timeline(light-grey) is selected from the entire timeline (dark-grey). This would make the data from the selected time to be visualized. This selection is made by left-clicking the mouse at the start of intended time (point A in the figure) and then right-clicking the mouse at the end of intended time (point B in the figure).

The blue lines in the timeline indicate the movement of the blue-coded object at that point of time.

Note: A & B are not part of the interface.

5. Timeline Zoom

To provide a better and effective control over the timeline operations, the user can zoom in and out of it using:

6. Object Selection

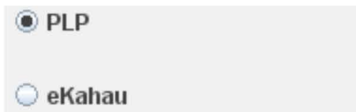
There might be more than one object in a building. So, user has the option to select which object(s) s/he wants to visualize.

This is a sample list of objects of a building. User can select multiple objects to visualize.

The objects are color coded and remains faithful in the timeline and visualization area.

7. Technology Selection

The tool records data using two different technologies i.e. PLP and eKahau. The interface gives an option to select the technologies whose recorded data needs to be visualized.



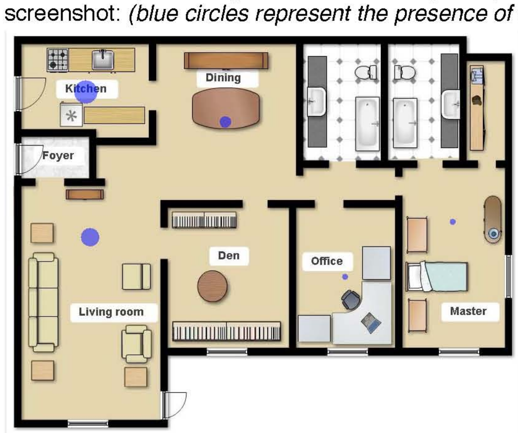
8. Type of Visualization

The data can be visualized in two ways:

a. Overview
b. Route

The following interface is used to choose between the two:

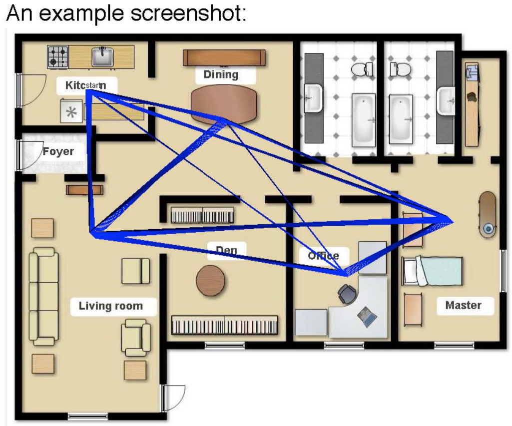
In the Overview mode, the areas in the floorplan have circular patterns with size of the circle representing the time the object spent at that location. An example screenshot: *(blue circles represent the presence of Marie at different locations)*



In the Route mode, the whole route of the object is shown. The direction of motion is represented by the arrow shaped movement marker:

The above shown marker signifies motion from left to right.

An example screenshot:



9. Animation

To give a more detailed and clear view of the movement of the object, an option to animate the route is given. The animation can be started by pressing Animate

Animation can be paused by pressing Pause
Pressing the same button again resumes the animation.

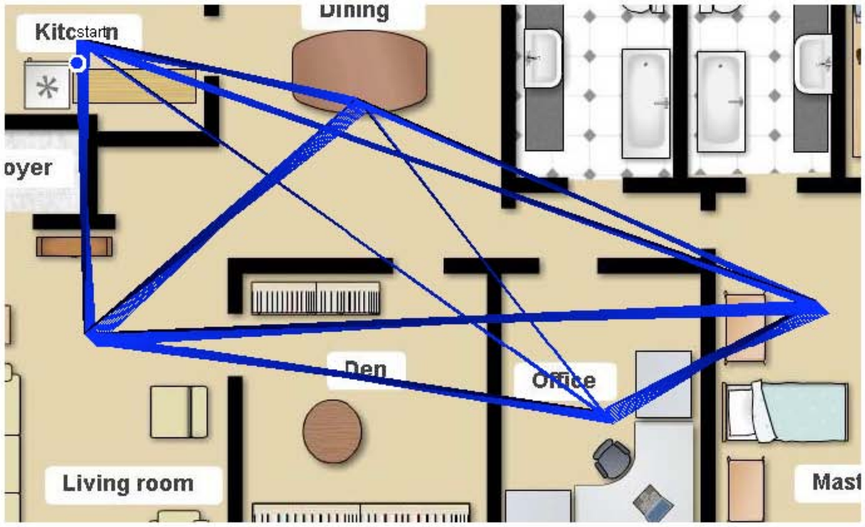
Stop can be pressed to stop the animation. This makes the application to ignore the progress of animation and if started again, the animation starts from the beginning.

A slider control:  can control the speed of the animation.

An option of displaying the time of the current movement is also added. This is an optional feature and user can decide whether it is required or not. It is controlled by a checkbox:

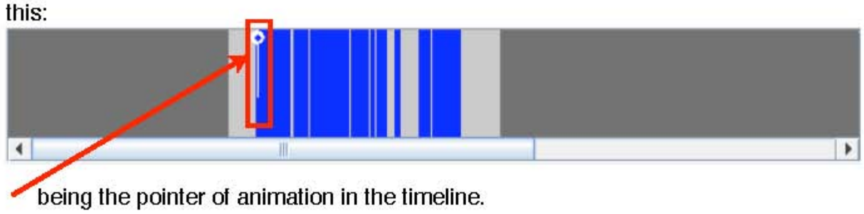
☐ View Animation Time

The animation screen looks something like this:



 being the animation peg for a blue color coded object.

The timeline also reflects the time of the currently animated movement. It looks like this:



being the pointer of animation in the timeline.

10. Annotation

A feature to let the user annotate the data is also provided. The annotations are time bound and hence, are reflected in the timeline.

This is the interface for notes.

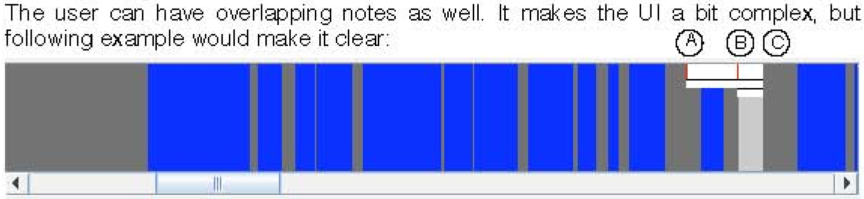
The note "Sleeping Time" would be added to the currently active time in the timeline if the user presses 

A note can be deleted by pressing 

A note can be updated by changing its text in the text field and then pressing 

The presence of a note is indicated on the timeline as a white rectangle.

Overlapping Notes
The user can have overlapping notes as well. It makes the UI a bit complex, but following example would make it clear:



The top most rectangle represents the presence of all the annotations (may or may not be overlapping). There will be red vertical lines in this rectangle representing start of a new annotation. To access the annotations user needs to click on the rectangle, and depending upon the location of click the enclosed annotations would be represented by narrower rectangles. In our example, if the user clicks between A and B, only one annotation peg would be visible as there is only one annotation at that point. But, if the user clicks between B and C, there will be 2 annotations pegs *(as shown in the included figure).* User needs to click on the appropriate peg to see its content in the text field.

APPENDIX C

PROXIMITY STUDY MATERIALS AND GUIDES

C.1 Deployment Checklist

The checklist used for each participant visit. The list includes all the tasks for each visit.

Phone Proximity Study Deployment Checklist

Subject ID: ____

First Meeting: **Date __________________________________**

_ Sign consent forms and vendor form
_ Give new phone plus charger
_ Copy contacts to new phone
_ Give tag plus charger and attachment
_ Explain when to charge tag (every 4 days)
_ Collect background information via interview
_ Schedule times for next 3 interviews
_ Explain procedure for interviews

First Interview: **Date __________________________________**

_ Charge tag
_ Give subject paper and ask them to reconstruct previous day
_ Download BT logs
_ Download phone log
_ Download GSM log
_ Run log parser
_ Bring up day visualization in Matlab
_ Walk through day with subject
_ Ask if there were any problems with the phone (*i.e.* tag/phone died)
_ Ask if day reviewed was typical
_ Ask about other atypical days and review data

Second Interview: **Date __________________________________**

_ Charge tag
_ Give subject paper and ask them to reconstruct previous day
_ Download BT logs
_ Download phone log
_ Download GSM log
_ Run log parser
_ Bring up day visualization in Matlab
_ Walk through day with subject
_ Ask if there were any problems with the phone (*i.e.* tag/phone died)
_ Ask if day reviewed was typical
_ Ask about other atypical days and review data

Third interview: **Date** ___________________________________

- _ Charge tag
- _ Give subject paper and ask them to reconstruct previous day
- _ Download BT logs
- _ Download phone log
- _ Download GSM log
- _ Run log parser
- _ Bring up day visualization in Matlab
- _ Walk through day with subject
- _ Ask if there were any problems with the phone (*i.e.* tag/phone died)
- _ Ask if day reviewed was typical
- _ Ask about other atypical days and review data
- _ Collect all equipment
- _ Pay subjects

C.2 Background and Initial Survey

This section includes the initial survey administered during the first visit. The aim was to get a sense of the participant's current practices with their mobile phone.

Phone Proximity Study First Meeting
Background Interview Questions

Date: ____

Subject ID: ____

1. What type of service plan do you have? How many minutes per month do you pay for? How many do you use?

2. Do you use a phone at home, or is your cell phone your primary phone?

3. What other applications do you typically use on your phone, if any? (*e.g.* camera, calendar, text messaging, web browsing)

___ camera ___ alarm clock
___ calendar ___ check email
___ text messaging ___ bluetooth communications
___ web browsing ___ calculator
___ games ___ to do list/notes
___ voice recorder ___ other (specify ________________________________)

4. How many hours per day would you estimate you have your phone with you? Does that differ on a weekend?

5. What is your current charging pattern? Do you charge it when the battery dies? Every night?

6. How often do you talk on your phone during the day? Week? Month? Who do you typically talk to?

7. Do you ever use the silent/vibrate mode on your phone? For what situations?

8. When you have your phone with you, how do you carry it? Wear it attached to a belt clip? In a purse? In a pocket?

9. What types of accessories do you use with your phone? (*e.g.* hands free set, car charger, belt clip). Do any of them use Bluetooth?

10. Do you use your phone for work purposes, personal use, or both? What percentage of each?

11. Can you provide a general sense of how you work throughout the day? One desk for the day? Move around a lot within a building? Move around a lot through multiple buildings?

12. Can you provide a general sense of the layout of your house? Is it a house, apartment, condo? How many people live in your house? What is its approximate size?

C.3 Day Reconstruction

This section includes a sample day reconstruction table that was given to the participants to fill out. They were asked to fill out as much as possible for the previous 24 hours during the visit.

Phone Proximity Study – Day Reconstruction

Subject ID ______________________________ Date ___________________________

Time	Activity	Phone Location	Your Location
12:00 AM			
12:30 AM			
1:00 AM			
1:30 AM			
2:00 AM			
2:30 AM			
3:00 AM			
3:30 AM			
4:00 AM			
4:30 AM			
5:00 AM			
5:30 AM			
6:00 AM			
6:30 AM			
7:00 AM			
7:30 AM			
8:00 AM			
8:30 AM			
9:00 AM			
9:30 AM			
10:00 AM			
10:30 AM			
11:00 AM			

Time	Activity	Phone Location	Your Location
11:30 AM			
12:00 PM			
12:30 PM			
1:00 PM			
1:30 PM			
2:00 PM			
2:30 PM			
3:00 PM			
3:30 PM			
4:00 PM			
4:30 PM			
5:00 PM			
5:30 PM			
6:00 PM			
6:30 PM			
7:00 PM			
7:30 PM			
8:00 PM			
8:30 PM			
9:00 PM			
9:30 PM			
10:00 PM			
10:30 PM			
11:00 PM			
11:30 PM			

Tag Recharging Schedule

February 8, 2006 ________________________________
February 9, 2006 ________________________________
February 10, 2006 ________________________________
February 11, 2006 ________________________________
February 12, 2006 ________________________________
February 13, 2006 ________________________________
February 14, 2006 ________________________________
February 15, 2006 ________________________________
February 16, 2006 ________________________________
February 17, 2006 ________________________________
February 18, 2006 ________________________________
February 19, 2006 ________________________________
February 20, 2006 ________________________________
February 21, 2006 ________________________________
February 22, 2006 ________________________________
February 23, 2006 ________________________________
February 24, 2006 ________________________________
February 25, 2006 ________________________________
February 26, 2006 ________________________________
February 27, 2006 ________________________________
February 28, 2006 ________________________________
March 1, 2006 ________________________________
March 2, 2006 ________________________________
March 3, 2006 ________________________________
March 4, 2006 ________________________________
March 5, 2006 ________________________________
March 6, 2006 ________________________________
March 7, 2006 ________________________________
March 8, 2006 ________________________________
March 9, 2006 ________________________________
March 10, 2006 ________________________________
March 11, 2006 ________________________________
March 12, 2006 ________________________________

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